

Mannava V. K. Sivakumar
James Hansen

Editors

Climate Prediction and Agriculture

Advances and Challenges



World
Meteorological
Organization
Weather • Climate • Water



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Mannava V. K. Sivakumar · James Hansen (Eds.)

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With 102 Figures and 55 Tables



World Meteorological Organization



Global Change System for Analysis,
Research and Training



The International Research Institute
for Climate and Society

 Springer

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Foreword

It is estimated that hunger is currently affecting one out of every seven people on planet Earth. Projections show that unless the world community is prepared to undertake intensive and sustained remedial action over a long-term, there could still be almost 700 million people chronically undernourished by the year 2010, with over 300 million in sub-Saharan Africa alone. Agriculture and its associated industries are primary sources of food and a major employment sector in most developing countries.

Climate change, and increasing climate variability, as well as other global environmental issues such as land degradation, loss of biological diversity and stratospheric ozone depletion, threaten our ability to meet the basic human needs in adequate food, water and energy, safe shelter and a healthy environment. To address these challenges, it is important to integrate the issues of climate variability and climate change into resource use and development decisions. Decreasing the vulnerability of agriculture to natural climate variability through a more informed choice of policies, practices and technologies will, in many cases, reduce its long-term vulnerability to climate change. For example, the introduction of seasonal climate forecasts into management decisions can reduce the vulnerability of agriculture to floods and droughts caused by the El Niño-Southern Oscillation (ENSO) phenomena.

In order to address the challenges facing sustainable agricultural development, the World Meteorological Organization (WMO) gives priority to the timely and effective implementation of some of the activities of its World Climate Programme, in particular the Agricultural Meteorology Programme and the Climate Information and Prediction Services (CLIPS) project, to ensure that progress made in the seasonal to interannual climate prediction is translated into field applications to ensure food security. In this regard, the Commission for Agricultural Meteorology (CAGM) of WMO has recommended that weather and climate forecasts should be increasingly tailored towards the requirements of agriculture in order that farmers can make their decisions with greater confidence.

The Climate Prediction and Agriculture (CLIMAG) interdisciplinary project was established in 1998 with the goal to demonstrate the practical utility of climate forecasts in agricultural decision-making. CLIMAG builds on the advances made in several areas especially in the science of climate forecasting, downscaling large area climate

forecasts to local applications, integration of climate forecasts in operational crop models to develop alternative scenarios for operational decision making, and capacity building at the local level in all these areas. Needless to say, there are numerous challenges in all these areas.

The use of climate information and prediction products in planning agricultural activities has become very useful in some parts of the globe especially developing countries, as was demonstrated by the CLIMAG pilot projects carried out in South Asia and West Africa over the past four years.

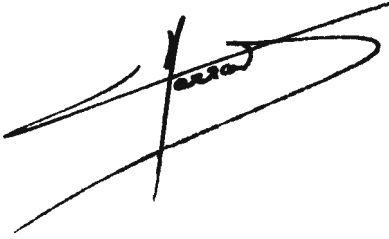
Furthermore, the Global Change System for Analysis, Research and Training (START) initiated the Advanced Training Institute on Climatic Variability and Food Security in July 2002 to equip young professionals from developing country with expertise in agriculture and food security to apply advances in climate prediction to their home institutions' ongoing efforts to address climate-sensitive aspects of agricultural production, food insecurity and rural poverty. Following this training institute, seed grants were provided with funding from the Lucille-Packard Foundation for follow-up project work on aspects of climate and food security in 14 countries.

It is with this background that, WMO, START and the International Research Institute for Climate and Society (IRI) organized an "International Workshop on Climate Prediction and Agriculture – Advances and Challenges" from 11 to 13 May 2005 at WMO in Geneva, Switzerland. The main objective of this workshop was to review advances in the application of seasonal climate prediction in agriculture over the past 5 years, and identify challenges to be addressed in the next 5–10 years to further enhance operational use of climate prediction in agriculture in developing countries.

Prior to the International Workshop, participants in the David and Lucille Packard Foundation-funded project on climate variability and food security were convened at a "Synthesis Workshop of the Advanced Institute on Climatic Variability and Food Security" from 9 to 10 May 2005 at WMO in Geneva to present their results, share their experiences, and synthesize lessons learned. The workshop was made possible through generous support from the Packard Foundation, the Asian Pacific Network (APN), the Inter-American Institute for Global Change Research (IAI), the National Oceanic and Atmospheric Administration/Office of Global Programs (NOAA/OGP), the Netherlands Ministry of Foreign Affairs (DGIS), the International START Secretariat (START), the World Meteorological Organization (WMO), and the International Research Institute for Climate and Society (IRI).

This volume, which brings together the papers presented at the International Workshop and the Synthesis Workshop, presents a good synthesis of the advances made so far in seasonal climate predictions and their applications for management and decision-making in agriculture, and identifies the challenges to be addressed in the next 5 to 10 years to further enhance operational applications of climate predictions in agriculture, especially in the developing countries.

We hope that this volume will serve as a major source of information to all services, agencies and organizations at national, regional and global level involved in promoting operational applications of climate predictions in agriculture.



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Preface

The Climate Prediction and Agriculture (CLIMAG) project started ten years ago under the auspices of the Global Change System for Analysis, Research and Training (START), the World Climate Research Programme (WCRP), the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme of Global Environmental Change (IHDP) was based on the increasing capacity to model crop growth and yield coupled with the improving ability of meteorologists to provide short- and medium-term weather forecasts. The CLIMAG Task Force, appointed by the START Scientific Steering Committee, developed a dynamic strategic plan which formed the basis for the First International Workshop on CLIMAG which was held from 27 to 29 September 1999 at WMO in Geneva.

The First International Workshop on CLIMAG considered a number of important issues relating to climate prediction applications in agriculture including capabilities in long-term weather forecasting for agricultural production, down-scaling, scaling-up crop models for climate prediction applications, use of weather generators in crop modeling, economic impacts of shifts in ENSO event frequency and strengths and economic value of climate forecasts for agricultural systems.

Much work has been done on various issues related to CLIMAG since September 1999 when the First International Workshop on CLIMAG was held. The International Research Institute on Climate Prediction (IRI) was engaged in many of the activities envisaged under the original CLIMAG work plan. Regional CLIMAG demonstration projects in South Asia and West Africa made considerable progress. A number of research projects were organized under the David and Lucille Packard Foundation-funded project on climate variability and food security. The AIACC project of START is supporting a number of regional projects dealing with assessment of adaptations to climate change impacts on the agriculture sector. NOAA-OGP has supported a number of other individual research projects.

The goal of the START, WMO and the International Research Institute for Climate and Society (IRI) sponsored "International Workshop on Climate Prediction and Agriculture – Advances and Challenges" held at WMO, Geneva from 11 to 13 May 2005 was to review the advances made so far in seasonal climate predictions and their applications for management and decision-making in agriculture and identify the challenges to be addressed in the next 5 to 10 years to further enhance operational

applications of climate predictions in agriculture, especially in the developing countries. Specific objectives of the workshop were:

- to summarize/synthesize the current status of seasonal climate predictions and their applications to small holder agriculture in different parts of the world (with emphasis on advances since the 1999 CLIMAG workshop);
- to identify the ways and means to promote the more active use of seasonal to inter-annual climate forecasts in agricultural planning and operations for the benefit of smallholder agriculture and rural livelihoods in developing countries;
- to develop an effective strategy for the communication and coordination of climate applications to a broader network of users at all levels i.e. agricultural education and research, agricultural extension and farming community (with some emphasis on the Consultative Group on International Agricultural Research (CGIAR));
- to discuss the ways of promoting regional agrometeorological research in order to provide an improved understanding of the interactions between climate processes and their complex linkages with agricultural production and food security.

Altogether there were 15 sessions (including the opening and closing session) in the workshop during which 18 invited papers were presented addressing the different specific objectives of the workshop. All the participants in the workshop were engaged in discussions on these papers and developed several useful recommendations for all organizations involved in promoting climate prediction and applications in agriculture, in particular in the developing countries.

Nine of the invited papers are appearing in a special supplement of *Climate Research* journal and a summary of all these papers is given in the first chapter of this volume. This volume includes eight other invited papers presented at the workshop as well as 18 papers presented by the participants in the David and Lucille Packard Foundation-funded project on climate variability and food security at the “Synthesis Workshop of the Advanced Institute on Climatic Variability and Food Security” held prior to the International Workshop describing the national case studies on CLIMAG.

As editors of this volume, we would like to thank all the authors for their efforts and for their cooperation in bringing out this volume in time. We are most grateful to Mr. M. Jarraud, the Secretary-General of WMO, Dr. Roland Fuchs, Director of the International START Secretariat and Dr. Steve Zebiak, Director General of The International Research Institute for Climate and Society for their continuous support and encouragement.

Mannava V. K. Sivakumar
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Editors

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Climate Prediction and Agriculture: Summary and the Way Forward

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1.1 Introduction

Agricultural production is highly dependent on weather, climate and water availability, and is adversely affected by weather- and climate-related disasters. Failure of rains and occurrence of natural disasters such as floods and droughts could lead to crop failures, food insecurity, famine, loss of property and life, mass migration, and negative national economic growth. Hence agricultural communities around the world have always looked for ways and means to cope with the climate variability including the use of various traditional indicators to predict the seasonal climate behavior.

In past two decades, significant advances have been made in the science and applications of seasonal climate forecasting. The principal scientific basis of seasonal forecasting is founded on the premise that lower-boundary forcing, which evolves on a slower timescale than that of the weather systems themselves, can give rise to significant predictability of atmospheric developments. These boundary conditions include sea surface temperature (SST), sea-ice cover and temperature, land-surface temperature and albedo, soil moisture and snow cover, although they are not all believed to be generally of equal importance. Climate variations, also called anomalies, are differences in the state of the climate system from normal conditions (averaged over many years, usually a 30-year period) for that time of the year. The strongest evidence for long-term predictability comes largely from the influence of persistent SST anomalies on the atmospheric circulation which, in turn, induces seasonal climate anomalies.

The Climate Prediction and Agriculture (CLIMAG) is an interdisciplinary program of research that builds on the advances made in several areas especially in the science of climate forecasting, downscaling large area climate forecasts to local applications, integration of climate forecasts in operational crop models to develop alternative scenarios for operational decision-making to minimize the impacts of climate risks and maximize the benefits to farming community, and capacity building at the local level in all these areas. Needless to say, there are numerous challenges in all these areas.

The CLIMAG project initiated after the International Workshop on CLIMAG held in Geneva in September 1999 (Sivakumar 2000) was based on the premise that advantage should be taken of current data bases, increasing climate knowledge and improved prediction capabilities to facilitate the development of relevant climate information and prediction products for applications in agriculture to reduce the negative impacts due to climate variations and to enhance planning activities based on the developing capacity of climate science. To review advances in application of seasonal climate prediction in agriculture over the past 5 years, and identify challenges to be addressed in the next 5–10 years to further enhance operational use of climate prediction in agri-

culture in developing countries, the Global Change System for Analysis, Research and Training (START), the World Meteorological Organization (WMO) and the International Research Institute for Climate and Society (IRI) organized an “*International Workshop on Climate Prediction and Agriculture – Advances and Challenges*” from 11 to 13 May 2005 at WMO in Geneva, Switzerland. Nine invited papers (Doblas-Reyes et al. 2006; Hansen et al. 2006; Msangi et al. 2006; Meinke et al. 2006; Roncoli 2006; Rubas et al. 2006; Sivakumar 2006; Thornton 2006; Vogel and O’Brien 2006) presented at this International Workshop were published in a special supplement of *Climate Research* journal (Hansen and Sivakumar 2006). This chapter presents a short summary, based primarily upon these nine papers, of the progress made so far in CLIMAG research, and suggests a way forward.

1.2 Predicting Climate Fluctuations and Agricultural Impacts

The key weather variables for crop prediction are rainfall, temperature and solar radiation, with humidity and wind speed playing also a role. As Doblas-Reyes et al. (2006) explained, seasonal climate forecasts are able to provide insight into the future climate evolution on timescales of seasons and longer because slowly-evolving variability in the oceans significantly influences variations in weather statistics. The climate forecast community is now capable of providing an end-to-end multi-scale (in space and time) integrated prediction system that provides skilful, useful predictions of variables with socio-economic interest.

Seasonal forecasts can be produced using mathematical models of the climate system. A wide range of forecast methods, both empirical-statistical techniques and dynamical methods, are employed in climate forecasting at regional and national levels (WMO 2003). Operational empirical-statistical methods, based on statistical links between current observations and weather conditions some time in the future, include analysis of general circulation patterns; analogue methods; time series, correlation, discriminant and canonical correlation analyses; multiple linear regression; optimal climate normals; and analysis of climatic anomalies associated with ENSO events. Dynamical methods (used principally in major international climate prediction centers) are model-based, using atmospheric GCMs in a two-tiered prediction system, or dynamically coupled atmosphere-ocean GCMs. These dynamical forecast models – an extension of the numerical methods used to predict the weather a few days ahead – are based on systems of equations that predict the evolution of the global climate system in response to initial atmospheric conditions, and boundary forcing from the underlying ocean and land surfaces.

Doblas-Reyes et al. (2006) emphasize the importance of a fully probabilistic approach during all the stages of the forecasting process. Predictions of the climate system evolution in seasonal timescales suffer mainly from two sources of uncertainty: initial condition and structural model uncertainty (Doblas-Reyes et al. 2006). To address the first source of uncertainty, forecast models are run many times from slightly different initial conditions, consistent with the error to estimate the effect of this initial-condition uncertainty. One way to represent model uncertainty is to incorporate, within the ensemble, independently derived models, resulting in a multi-model ensemble system (Palmer et al. 2004). Hagedorn et al. (2005) and Doblas-Reyes et al. (2005)

showed that the DEMETER multi-model ensemble system, made up with 7 European coupled models, is intrinsically more useful and more skilful than forecasts from any one (e.g. national) model. “Forecast assimilation” deals with statistically combining multiple dynamical and statistical forecasts to maximize the content information (Stephenson et al. 2005).

For agriculture, climate forecasts must be interpreted in terms of production outcomes at the scale of decisions if farmers and other agricultural decision-makers are to benefit. Interest in linking seasonal climate forecasts from general circulation models (GCMs) with crop models is motivated by: (a) the need for information that is directly relevant to decisions, (b) use for *ex ante* assessment of potential benefits to enhance credibility and support targeting, and (c) support for fostering and guiding management responses to advance climate information (Hansen 2005).

At the time of the inaugural CLIMAG workshop in 1999, nearly all quantitative efforts to translate seasonal forecasts into agricultural terms and assess the value of management responses have used categorical indices of ENSO to select historic analog years as inputs to crop models. Interest in incorporating forecasts based on dynamic climate models were slowed by concerns about the difference in spatial and temporal scale of GCMs and crop models, and the dynamic, nonlinear, often non-monotonic relationship between meteorological variables and crop response. However, the past five years have seen increasing interest and some methodological advances in using dynamic climate model output as input to process-level crop models, synthetic daily weather or daily climate model output to drive the crop model; statistical transfer functions trained on crop model predictions run with historic weather data; and variations on the analog method that include weather classification, hidden Markov models and probability-weighted historic analogs (Hansen et al. 2006).

Several avenues are likely to enhance the quality of forecasts of agricultural impacts of climate variations over the next five to ten years. First, dynamically coupling crop models within climate models will support refined two-way interaction between the atmosphere and agricultural land use. Second, remote sensing and proliferation of spatial environmental databases provide substantial opportunities to expand the use and enhance the quality and resolution of climate-based crop forecasts. Finally, climate-based crop forecasts will benefit from climate research in the emerging area of “weather within climate.”

1.3

Effectiveness of Seasonal Forecasts and Climate Risk Management

Climatic shocks directly impact household economies, but also often aggravate other stresses, such as disease burden (e.g. HIV/AIDS) (Tango International 2005). Vogel and O’Brien (2006) argue that climate forecast information treated in isolation (e.g. in ‘stand alone’ climate outlook forums) and disseminated in a traditional, linear fashion from producer to user, ignores the broader, complex social context in which such information is embedded. The needs of users, the role of culture and the complex interactions of traditional knowledge systems and ‘external climate information’ require better understanding and articulation. According to Vogel and O’Brien (2006), preoccupation with dissemination issues often distracts the focus from the contextual situations in which these tools are embedded. The contextual environment in which end

users operate and use information is not neutral and egalitarian. End users, including farmers, usually operate in an environment of considerable uncertainty, reacting to and coping with multiple stressors and risks whose impacts are not always clear or predictable.

The way one interprets the linkages between climate, agriculture and food security fundamentally shapes the ways in which forecasts are usually 'framed', disseminated and eventually used. Recent investigations of the progress and outcomes of the Vulnerability Assessment Committees, established in 2002 in six countries to examine the food crisis in the Southern African region, have shown that measures of food gaps are not effective ways of capturing the causes of food insecurity in the region but that a wider, livelihoods-based perspective is required (Tango International 2005).

According to Vogel and O'Brien (2006), there is currently a disconnection between the climate information enterprise (e.g. modeling, forecast production, design, user-assessments, user needs and constraints to the uptake of forecast products) and the linkages and interplay with those operating in formal institutions (e.g. Departments of Agriculture, Water Affairs, Social Welfare, etc.) as well as informal institutions (e.g. welfare organizations, church groups, NGOs, humanitarian organizations, etc.). Hence greater attention needs to be given to what infrastructural and institutional advances are necessary to facilitate the use of forecast information within the livelihood strategies prevailing in a given region.

Cash and Buizer (2005) proposed that *salience* (the perceived relevance of the information), *credibility* (the perceived technical quality of the information) and *legitimacy* (the perceived objectivity of the process by which the information is shared) have a critical impact on how decision-makers accept and use information. From case studies from Australia, India and Brazil, Meinke et al. (2006) illustrate the influence that salience, credibility and legitimacy have on the degree to which end users embrace and apply what the climate science community has to offer, and how the nature of interactions with end users can either foster or damage these elements.

Meinke et al. (2006) illustrate salience in the context of efforts to reorient climate science to the questions that are relevant to Australian drought policy. Australian drought policy is focused on enhancing the self-reliance of farmers to manage climate risk. Self-reliance is intertwined with the vulnerability and resilience of the livelihoods of rural communities. Policy is largely powerless to influence the physical exposure of production systems to climate variability, but can enhance the resilience of rural livelihoods by influencing the diversity of assets and income sources from which rural livelihoods are derived, and flexibility to switch between them (Ellis 2000). Past scientific inputs to Australia's drought policy have focused on physical measures (e.g. variability in rainfall, soil water analysis and plant growth) of the extent to which rural communities are exposed to climate variability. These inputs are now expanding to include the human, social, natural, physical and financial assets from which resilient rural livelihoods are derived, and which policy can influence.

Credibility is discussed from the perspective of smallholder farmers in India. Experience with villages in southern India shows that intensive and costly interaction between researchers and rural communities can build the credibility of climate information. In this instance, the creation of credibility through stakeholder engagement bore the "seeds for its own destruction" by creating demand without a sustainable institutional mechanism to meet that demand beyond the life of the pilot project.

A well-documented case study from northeast Brazil illustrates the importance and fragility of legitimacy. The State of Ceará's Meteorology and Hydrology Service (FUNCEME) actively provides climate and related information to water resource managers and the region's agricultural community. The state government initiated a program, *Hora de Plantar* (Time to Sow), to distribute hybrid seed to smallholder farmers at the time when soil moisture conditions were supposedly adequate to ensure a good crop. Although the program was successful in some seasons, a perception that the program often distributed seeds too late to take advantage of early rain and, more importantly, disempowered farmers by transferring control of the decision-making process to government officials (Lemos 2003), weakened the legitimacy of both *Hora de Plantar* and FUNCEME. FUNCEME has recently made an effort to rebuild legitimacy by distancing itself from *Hora de Plantar*, implementing participatory activities with the agricultural sector, and producing their seasonal forecasts in collaboration with the International Research Institute for Climate and Society (IRI) and other international agencies that are independent of regional political interests.

1.4 Economics of Climate Forecast Applications

Rubas et al. (2006) presented a discussion on four methodologies economists use to model the decision-making process: decision theory, general equilibrium modeling, game theory, and mechanism design theory and suggested that climate forecast issues are ripe for more innovative and rigorous studies that can lead to theoretical advances in the economics of information as well as advances in climate sciences.

The most widely used form of decision theory assumes that preferences among risky alternatives can be described by maximizing net payoffs. The value of climate forecasts is the expected difference between the net payoffs when the forecasts are used to make optimal decisions, and the net payoffs when decisions are made optimally using only prior knowledge.

Game theory recognizes that the choices of individuals are interlinked. Unlike decision theory, in game theory, researchers must account for interactions between decision-makers and the combined effect their decisions may have on each other's payoffs.

General equilibrium modeling attempts to account for all decision-makers, all possible decisions, and their impacts on the market prices of all relevant commodities. Studies have used general equilibrium concepts to develop simpler partial equilibrium models, sector models, and trade models of particular crops to examine the effects of climate forecast use (Chen and McCarl 2000; Chen et al. 2002).

Decision theory, game theory, and general equilibrium modeling vary in the number of decision-makers and decisions modeled, but all assume that the rules of the process are fixed. In mechanism design, the rules players operate under become part of the process. In climate forecast applications, the goal is to find the set of market and institutional rules that maximize the net benefits associated with climate forecast use.

Rubas et al. (2006) explained that decision-making using climate forecasts has generally been treated by the social sciences as an applied issue and not as an issue that can be used to advance theory. She argued that combining research on technology

adoption, climate forecasts, and the economics of information would allow researchers to combine cutting-edge issues from different disciplines. Economic thinking applied to climate applications has already: (a) contributed to our understanding of how to incorporate uncertain information into decision-making, (b) proven to be a good bridge between the physical and social sciences and decision-makers, by translating climate-sensitive biophysical information into viable resource allocation choices, and (c) revealed the conditions under which decision-makers can benefit from climate information.

1.5 Assessing Adoption and Benefit

Ex ante impact assessment seeks to assess the potential outcomes of an innovation in advance of its adoption, while *ex post* assessment seeks to assess actual outcomes following adoption. The continually evolving tools of *ex ante* and *ex post* impact assessment, developed to assess the likely adoption and value of agricultural technology and innovation in general, are relevant to applications of climate forecasts. However, several characteristics of climate forecasts make assessment of their impacts particularly challenging. Forecasts are inherently probabilistic, and assessing their likely credibility to potential end-users over time is difficult (Ziervogel et al. 2005). In addition to long-term production impacts, they are likely to influence risk in a manner that is difficult to anticipate fully. Finally, if many producers in a region act on forecasts, impacts on commodity prices may be considerable.

Ex ante impact assessment serves the two-fold purpose of providing evidence to mobilize resources for a new innovation, and insight to inform targeting (Thornton 2006). Thornton argues that no single method is suitable for dealing with all situations, and calls for combining a range of quantitative and qualitative methods including: economic surplus methods, cost-benefit analysis, various forms of mathematical programming, econometric methods (treated in Alston et al. 1995), non-market valuation methods (Haab and McConnell 2002), integrated assessment, spatial analysis (including poverty mapping) (Hentschel et al. 2000), household and community studies involving formal and informal surveys, market studies, participatory technology development (Douthwaite et al. 2004), and a wide range of hard and soft simulation models (Thornton et al. 2003) are available.

Climate forecast impacts have to be assessed both in time (to account for the stochastic nature of climate and probabilistic nature of forecasts) and space (to account for market impacts of climate fluctuation and forecast use). Assessment should also identify the institutional and policy support that is likely to be required in a region, and estimate the costs of providing this support.

In contrast to *ex ante* approach, an *ex post* analysis would base its valuation on the observed actions of the economic agent and how he responded to the realized environmental shock or climate outcome. There are few, if any, regions in the developing world where rural communities have had access to operational climate information and support tailored to their needs, for sufficient time to allow *ex post* assessment of use and benefits. Msangi et al. (2006) argue that understanding current use of *ex post* impact assessment methodology for evaluation of agricultural research investments

will enable advocates of climate applications to collect baseline information and prepare to provide credible evidence of uptake and benefit as it occurs. Their survey highlights the use of econometric approach and economic surplus methods. As the econometric approach requires large amounts of data, which are not usually available, the economic surplus approach has been much more widely applied (Maredia et al. 2000).

Since the climate forecast predictions as well as the climate outcomes themselves are stochastic in nature, a more structurally-based model that models the agent's beliefs and how they change with information, would be able to account for this uncertainty more explicitly, and even capture the agent's attitudes toward uncertainty and risk. The structural behavioral analyses represent the state-of-the-art in behavioral modeling, and have the best chance of overcoming the confounding influences that could bias the valuation of climate information in *ex post* analyses. Structural estimation also allows the researcher to investigate the preferences of the decision-maker and to examine the role that risk-aversion plays in their actions.

1.6 Building on Farmers' Knowledge

Roncoli (2006) reviews ethnographic and participatory research methods, which involve intensive interaction with farmers or other stakeholders, that complement the quantitative economic research and assessment methods described in the preceding sections. This research provides rich insights into the cognitive and cultural landscape in which farmers' understanding of climate and climate information is grounded, and the decision-making process and environment that defines options, constraints, and outcomes.

Taxonomies, seasonal calendars, and ranking matrices of climate events have helped researchers to identify salient attributes that structure people's perceptions and experiences of climate (Orlove 2004; Ziervogel and Calder 2003), and highlight discrepancies between the ways farmers think about climate and the ways forecasts are formulated. For example, the seasonally averaged timeframe and regional scale typical of operational climate forecasts do not match farmers' concern with short-term, localized events (Hansen et al. 2004) or the duration and distribution of rainfall within the growing season (Roncoli et al. 2004). Narrowing this gap will necessitate bringing scientists' own cultural models into the analytical focus to understand how they shape the research agenda.

Ethnographic methods have shown that farmers around the world have a diverse repertoire of shared and specialized forecasting knowledge based on environmental observations and ritual practices. Field data show that farmers do not generally rely on a single indicator, but rather combine signs that arise at different times from various sources (Roncoli et al. 2002; Luseno et al. 2003). Although a dearth of long-term data series for local indicators, such as wild plants or insects, has hampered efforts to assess the validity of indigenous forecasts, innovative cross-disciplinary research, drawing from ethnographic, agronomic and atmospheric data, has established that Andean farmers' rainfall predictions based on the visibility of particular stars have a natural explanation and some skill (Orlove et al. 2002).

Risk communication research indicates that people's grasp of probability is often imperfect, as personal experience and communication practices can lead to cognitive biases. Yet interactive exercises during fieldwork and workshops have shown that farmers' ability to interpret probability and use forecasts in decision-making can improve with interaction and experience (Patt 2001). Field research has also shown that farmers' expectations and assessments of accuracy may differ for traditional and scientific forecasts (Nelson and Finan 2000).

The role of climate forecasts in rural livelihoods hinges on household vulnerability to climate risk. While quantitative methods make it possible to measure and compare levels of vulnerability, qualitative approaches provide valuable insights into subtler dimensions of vulnerability. In-depth interviewing and participant observation has revealed how gender, ethnicity, and caste can limit access and use of climate forecasts among African farmers (Roncoli et al. 2004). By combining participatory methods with quantitative surveys and agent-based modeling, a study among farmers in Southern Africa showed that, while wealthy households realized greater yield gains, climate forecasts benefited poor farmers the most by reducing the likelihood of food shortage (Ziervogel et al. 2005).

1.7 Way Forward

In his review of the current status and future challenges for climate prediction applications in agriculture, Sivakumar (2006) proposed several priorities to advance the use of forecasts for climate risk management in agriculture in the near future.

1.7.1 Improve the Accuracy of Prediction Models

Because the behavior of the atmosphere is chaotic, results from even well performing models can diverge, or develop increasing uncertainty at longer time ranges. Good science and support tools are fundamental prerequisites for ensuring a higher percentage of adoption of climate forecasts by farmers. As Doblaz-Reyes et al. (2006) explained, several avenues are likely to enhance the quality of forecasts of agricultural impacts of climate variations over the next five to ten years. First, dynamically coupling crop models within climate models will support refined two-way interaction between the atmosphere and agricultural land use. Resulting predictions will continue to require calibration for the foreseeable future. Second, remote sensing and proliferation of spatial environmental databases provide substantial opportunities to expand the use and enhance the quality and resolution of climate-based crop forecasts. Third, empirical evaluation across a range of crops and locations will help establish the robustness and relative merits of alternative approaches. The fourth area where we expect to see significant progress is in advancing consistent methods for assessing the uncertainties associated with climate-based crop forecasts. Finally, climate-based crop forecasts will benefit from climate research in the emerging area of "weather within climate."

1.7.2

Generate Quantitative Evidence of the Usefulness of Forecasts

Although there have been several case studies on the application of climate forecasts for better managing risks under a variable climate, wider and more consistent applications of the forecasts can only be promoted when more quantitative evidence can be generated about the usefulness of climate forecasts. Current research on climate forecast applications needs to focus more on impact assessment of climate forecasts through the development of new tools to assist in the evaluation of impacts of climate forecasts (Thorton 2006). These include the specification of comprehensive behavioral frameworks that go beyond current notions of risk theory, so that impacts on food security, reduction of vulnerability, and increases in household adaptive capacity can be addressed. A third area is in the development of hybrid approaches that combine the quantitative with the qualitative, the top-down with the bottom-up, and the socio-economic with the biophysical aspects. A fourth area is to make the process of impact assessment as participatory as possible.

1.7.3

Give Greater Priority to Extension and Communication

Hansen (2002) argued that sustained use of climate prediction to improve decisions depends on adequate communication. Proper communication of information implies that the user is receptive to “proper” channels i.e. sources that they already know and trust. Hence agricultural extension agencies must be involved from an early stage since they are in regular contact with farmers. Another aspect of the “proper” information is related to the communication process of translating the probabilistic forecasts into easily understandable language for the farmers. Improper interpretation of the probabilities can lead to loss of trust and exposing farmers to unnecessary risks. Appropriate and beneficial production decisions are often related to timing and hence the communication of climate forecast information also must also be made in a timely manner.

1.7.4

Respond to Users’ Needs and Involve Them More Actively

The use of climate forecasts requires that right audience receives and correctly interprets the right information at the right time, in a form that can be applied to the decision problem(s). Understanding who the potential clients are, what characterizes them, how they are linked to relevant and appropriate institutions, how information flows between the major actors in the system – these are questions that can be answered with solid baseline information, and improvements in spatial and non-spatial databases will help greatly in more effective targeting of potential forecast users (Thorton 2006). Forecasts are only useful if they are skillful, timely and relevant to actions, which potential users can incorporate into production decisions to improve potential outcomes (Stern and Easterling 1999). Roncoli (2006) advocates the use of ethnographic

and participatory methods to provide a roadmap through the intricacies of climate information processing and agricultural decision-making and to help enhance the role that climate forecasts can play in improving rural livelihoods. Ethnography must go beyond portrayals of culture as a static configuration of categories and norms uniformly shared across society, to account for social diversity and cultural change. It also needs to extend its scope to elucidate the workings of culture in scientific circles as well as in rural communities. Likewise, participatory research should go beyond the deployment of a fixed repertoire of tools and techniques. It needs to examine the participation process itself through ethnographic and sociolinguistic analysis of group dynamics, including the interactions between farmers and scientists. It has been demonstrated that when stakeholders are well informed about the utility of climate prediction information and when they are more directly involved in testing the benefits of such information, they tend to offer more direct support for climate prediction applications.

1.7.5

Learn From Non-Adoption Situations

As Rubas et al. (2006) explained, improved climate forecasts are relatively new, so there has been little research on the adoption path over time or the optimal levels of adoption. It is important that when efforts are made to promote adoption by rural communities, plans for studying the reasons for non-adoption are built into the project implementation framework. Reasons for the adoption or otherwise of new technologies can be identified through farmer surveys, model-based analysis of farming systems, and through studying farmer motivations and behavior. Combining research on technology adoption, climate forecasts, and the economics of information would allow researchers to combine cutting-edge issues from different disciplines. Such research could build on the important survey studies on the use of climate forecasts by decision-makers.

1.7.6

Create Better Institutional and Policy Environment

As Rubas et al. (2006) explained, climate information in isolation has relatively little value beyond basic science unless it is integrated into managerial and policy processes. This requires an integrated research program that robustly interacts with and identifies the needs and environment in which decision-makers function. One of the major challenges to promotion of climate forecast applications in most of the economic sectors at the national level is the lack of a clear national climate agenda. Absence of appropriate policy documents leads to problems such as lack of a clear guidance as to which institutions have the main responsibility to produce and distribute climate products, inadequate research capacity and lack of a critical mass to deal with the key climate issues.

An important policy implication is that climate information and forecasts can be combined with research from other physical and social sciences to mitigate natural disasters by helping financial institutions, development agencies, and insurance corporations better identify resiliency strategies that enhance development and reduce risk. Climate change is another area that can benefit from seasonal forecast research. There is increasing recognition that economic analysis of climate change must occur

at a finer spatial scale. Research on climate forecasts as an adaptation strategy for climate change holds great promise. Education in general as well as education on using climate forecasts is closely related to this issue and provides yet another place to look for research that can be combined with climate forecast research to advance the economics of information and lead to a better understanding of the decision to adopt climate forecasts (Rubas et al. 2006).

1.7.7

Derive Economic Benefit through Applications to Trade and Storage

According to Hallstrom (2001), trade and storage are especially important instruments for responding to agricultural production shocks caused by climate variation. Trade can mitigate the negative impacts of a climatic disturbance in a given location by allowing demands to be met by production that took place elsewhere. Similarly, storage allows demands at one point in time to be met by production that occurred at an earlier point in time.

1.8

Conclusions

Considerable advances have been made in the past decade in our collective understanding of climate variability and its prediction in relation to the agricultural sector and scientific capacity in this field. There is a clear need to further refine and promote the adoption of current climate prediction tools. It is equally important to identify the impediments to further use and adoption of current prediction products.

There is a need to further improve the models to enhance the skill in predicting smaller fluctuations which often concern the users at the field level. The issue of downscaling current predictions to facilitate more accurate local applications continues to be a challenge. Active collaboration between climate forecasters, agrometeorologists, agricultural research and extension agencies in developing appropriate products for the user community is essential.

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Climate Downscaling: Assessment of the Added Values Using Regional Climate Models

L. Sun · M. N. Ward

2.1 Introduction

The science and practice of seasonal climate forecasts have progressed significantly in the last couple of decades (Carson 1998; Goddard et al. 2001; Palmer and Anderson 1994). It has been demonstrated that seasonal forecasts are skillful in many regions, particularly in the tropics (Goddard et al. 2003; Gong et al. 2003; Stockdale et al. 1998). General circulation models (GCMs) have been employed in seasonal climate forecasting at various centers (Derome et al. 2001; Frederiksen et al. 2001; Mason et al. 1999; O'Lenic 1994; Ward et al. 1993). Due to computational constraints, GCMs typically are run at relatively coarse spatial resolutions generally greater than 2.0° for both latitude and longitude. The direct result of the poor spatial resolution of GCMs is a serious mismatch of spatial scale between the available climate forecasts and the scale of interest to most climate forecast users. Some applications also require climate forecasts with higher temporal resolution. Most crop models, for example, require daily weather input. GCM outputs are available as the required daily values, but GCM daily precipitation shows very low daily variability and many high errors compared to observations (Mearns et al. 1990).

Climate downscaling is a critical component linking prediction to application. In recent years, increasing attention has been given to the dynamical downscaling problem; that is, a relatively high resolution regional climate model (RCM) is driven by a low resolution global climate model. The hypothesis behind the use of high-resolution RCMs is that they can provide meaningful small-scale features over a limited region at affordable computational cost compared to high-resolution GCMs.

Since Dickinson et al. (1989) and Giorgi (1990) first demonstrated that RCMs could be used for climate study, RCMs have been extensively tested for climate downscaling over many regions of the world (Fennessy and Shukla 2000; Giorgi and Marinucci 1991; Hong et al. 1999; Kanamitsu and Juang 1994; Nobre et al. 2001; Roads 2000; Seth and Rojas 2003; Sun et al. 1999a,b; Takle et al. 1999). Many issues concerning the use of nested RCMs as a climate downscaling technique have received considerable attention, such as, spatial resolution difference between the driving data and the nested model (Denis et al. 2003; Nobre et al. 2001), domain choice (Landman et al. 2005; Seth and Giorgi 1998), model spin-up (Anthes et al. 1989; Giorgi and Mearns 1999), update frequency of the driving data (Juang and Kanamitsu 1994), quality of the driving data (Miguez-Macho et al. 2004), horizontal and vertical interpolation errors (Bielli and Laprise 2006), physical parameterization consistence (Giorgi and Mearns 1999), climate draft or systematic errors (Roads and Chen 2000), etc.

It is not the purpose of this chapter to provide a review of the current status of climate dynamical downscaling. Rather, the primary objective of this chapter is to assess the added values of climate dynamical downscaling at seasonal time scale. Section 2.2 focuses on improved spatial patterns and climatologies. Section 2.3 discusses the climate predictability at smaller spatial and temporal scales, Sect. 2.4 evaluates dynamical downscaling forecasts, and Sect. 2.5 raises some further issues for improvement of the climate dynamical downscaling.

2.2

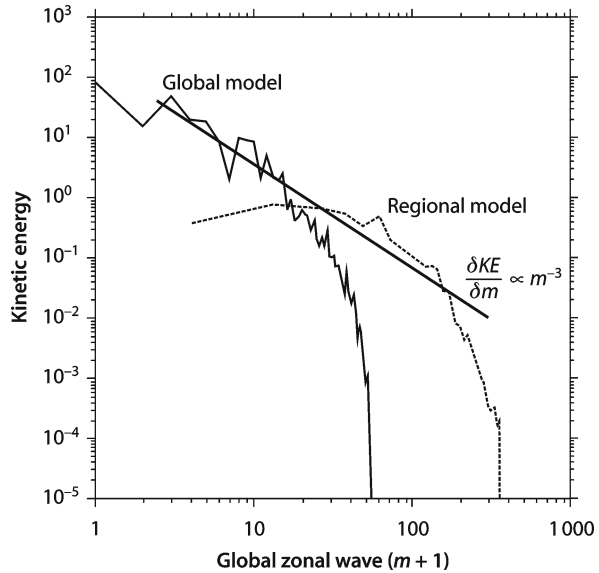
Smaller Spatial Scales

Smaller spatial scale features developed in regional models are attributed to four types of sources: (1) the surface forcing, (2) the nonlinearities presented in the atmospheric dynamical equations, (3) hydrodynamic instabilities, and (4) the noise generated at the lateral boundaries and model errors. A better representation of small scale forcings such as topography and other surface heterogeneities (type 1) contributes to the increase of details in high-resolution simulations. The nonlinear dynamics (type 2) also play an important role. Internal atmospheric dynamics exhibits a nonlinear downscale cascade by stirring and stretching the flow, and this phenomenon would occur even in the absence of surface forcings. Shear and buoyancy in the flow can also, through hydrodynamic instabilities (type 3), produce mesoscale features without the help of surface forcings. The high resolution used by RCMs allows for a better representation of these three types of sources, in addition to the increased accuracy of the numerical scheme employed to solve the governing equations of the climate system. However, the noise introduced at the lateral boundaries and the model errors (type 4) may contaminate the simulations and forecasts.

Typical spectral distributions of the global model and the regional model are shown in Fig. 2.1 (Chen et al. 1999). After a relatively flat planetary wave portion of the kinetic energy spectrum, the global model shows a rapid drop-off with the -3 power law of geostrophic motion (Phillips 1963). Because of the strong artificial small-scale diffusion, an even more rapid drop-off occurs near the end of the global model resolution (i.e. T62 in this case) due to the strong small-scale diffusive damping in the model. The kinetic energy spectrum of the regional model is projected to the global zonal wave number. The regional model simulation with higher resolution continues to follow the -3 power drop-off until the end of the regional model resolution (i.e. wave 300 in this case), when another diffusion induced rapid drop-off occurs. The added value of the regional model in this case is that it can resolve the waves with wave numbers 30–300.

Over lands, denser grid spacing in regional models obviously improves the resolution of the terrain, and better represents the land use (type 1 of the sources). The surface forcing is thought to be the one that RCMs exploit the most because of heterogeneity of the land surface. An example is shown in Fig. 2.2. The climatology of precipitation over Kenya for observations is compared with that from an ensemble of three GCM runs at T42 spectral truncation (approximately 2.8 degrees resolution) and a nested regional model at 80 km and 20 km resolution, respectively. The GCM is the ECHAM GCM developed at Max Planck Institute for Meteorology (MPI, Roeckner et al. 1996),

Fig. 2.1. Regional (dashed line) and global (thin solid line) model kinetic energy (KE) spectra for January 1993. The global model spectra are only averaged over the latitude bands covering the regional domain, while the regional spectra are projected over to the global with respect to global zonal wavenumber (actually $m + 1$ so that the $m = 0$ can be included on this logarithmic plot). The thick solid line represents a theoretically predicted energy cascade curve (Chen et al. 1999)



and the regional model is the regional spectral model (RSM) developed at National Centers for Environmental Prediction (NCEP) (Juang and Kanamitsu 1994). The observations are interpolated to $20 \text{ km} \times 20 \text{ km}$ grids using 453 station data. The GCM cannot resolve the observed local precipitation maxima around Lake Victoria and over Kenya highland. The regional model at 80 km resolution can “see” Lake Victoria (i.e. 15 grids on Lake Victoria), and produces the local precipitation maximum around the lake. But it fails to generate the local precipitation maximum over Kenya highland because the horizontal gradient of the terrain at 80 km resolution is not strong enough. The regional model at 20 km resolution represented Lake Victoria well with more than 200 grids, and raises the height of Kenya highland by approximately 2 000 meters higher compared to the GCM, thus significantly increases the horizontal gradient of the terrain relative to the GCM. As expected, it is able to generate the two observed local precipitation maxima.

Over oceans, denser grid spacing in regional models mainly exploits the types 2 and 3 of the sources (list in first paragraph of this section). A typical tropical cyclone in the regional model and the global model are illustrated in Figs. 2.3 and 2.4, respectively. The GCM resolution is about 280 km and the regional model resolution is 50 km. Higher resolution leads to a much finer representation of the 850 hPa vorticity in the regional model compared to the driving GCM. The maximum vorticity near the center of the storm is much higher than that of the driving GCM. The maximum wind speed is higher in the regional model, and there is a clear minimum near the center of the storm, an attempt by the regional model to produce the storm’s “eye.” Precipitation and humidity values are also higher in the regional model, and there appears to be a rain band that is not present in the GCM simulation. Therefore, the high-resolu-

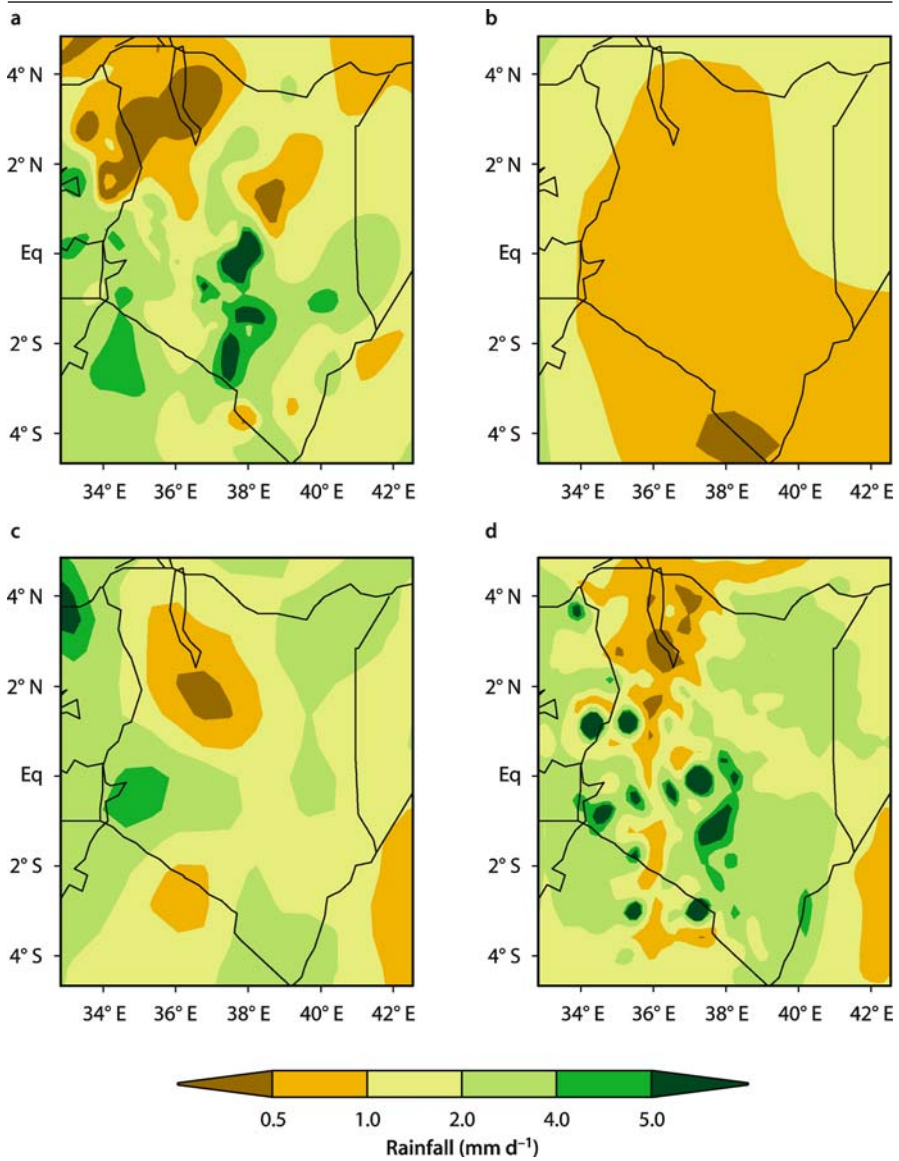


Fig. 2.2. October-November-December precipitation averaged for 1970–1995; **a** observation; **b** ECHAM GCM ensemble mean; **c** ensemble mean of the ECHAM-RSM first nesting (resolution of 80 km); **d** ensemble mean of ECHAM-RSM double nesting (resolution of 20 km). The precipitation unit is mm day^{-1}

tion regional model gives a representation of the tropical cyclone that is much more similar to the reality than that obtained by a coarse global model.

To date, it is widely accepted that dynamical downscaling improves spatial patterns and climatologies as compared to the coarse resolution GCMs.

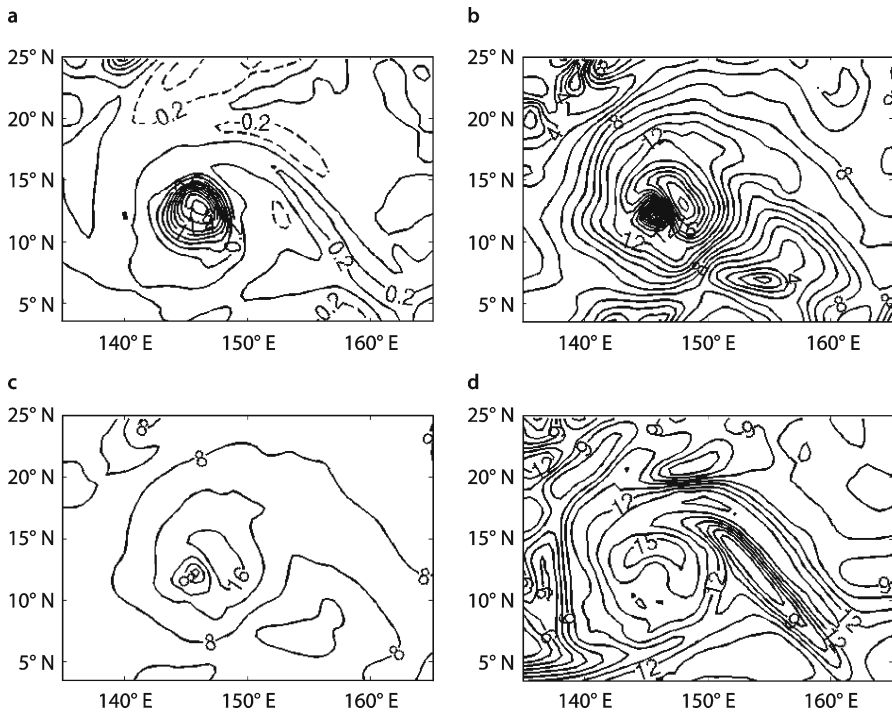


Fig. 2.3. Typical fields of a tropical cyclone in the regional model; **a** vorticity at 850 hPa ($\times 10^{-4} \text{ s}^{-1}$); **b** wind speed at 1000 hPa (m s^{-1}); **c** precipitation (mm per 6 hours); **d** specific humidity at 850 hPa (g kg^{-1}) at 14 June 1994 00:00 GMT (Camargo et al. 2007)

2.3 Predictability at Smaller Spatial and Temporal Scales

Dynamical downscaling has been performed in many regions (e.g. Castro et al. 2005; Misra et al. 2003; Roads et al. 2003; Sun et al. 1999a,b). Most of these investigations are case studies (e.g. simulations of wet and dry years or warm and cold years). To answer the question of whether predictability of climate systems is improved by dynamical downscaling is to use multiple GCMs with multiple ensembles and force multiple regional models (Leung et al. 2003). This task exceeds our current computational limits, and has not been accomplished for any regions yet. An attempt is made to shed light on this by the 30-year multiple ensembles of one GCM, the ECHAM4.5 GCM (T42), and one RCM, the RSM, with resolution of 60 km for northeast Brazil (the Nordeste) (Sun et al. 2005). The primary objectives are to find out: (1) whether the finer spatial scale information produced in the regional model is skillful, or is it just ‘noise’ on top of the large-scale signal? and (2) whether the temporal character of variability is skillful in the regional model?

A spatial scale separation technique is applied to analyze the added value of the RCM compared with the GCM. The observed and RCM simulated precipitation is

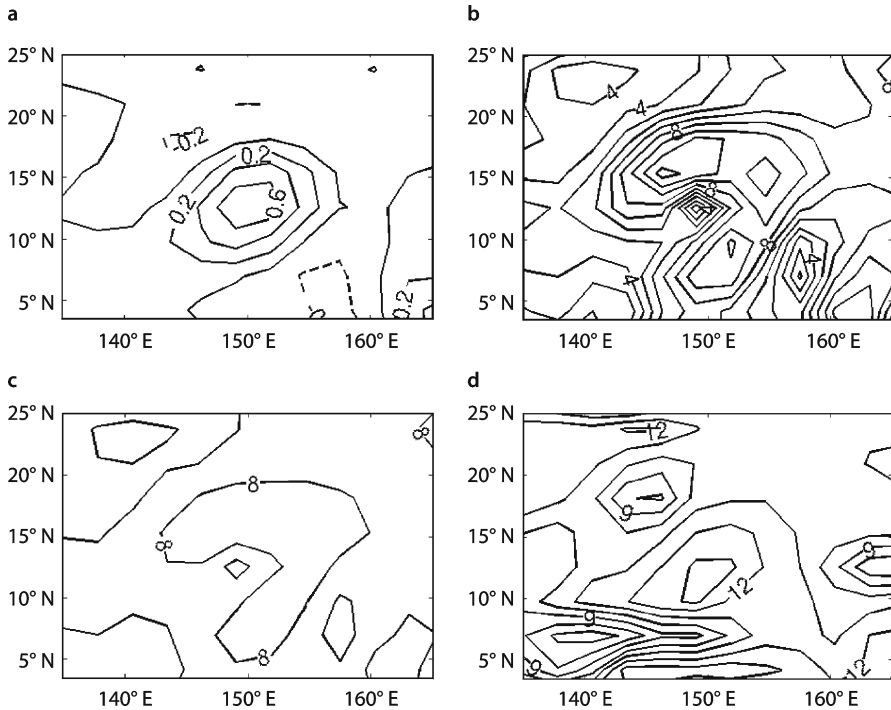


Fig. 2.4. Typical fields of a tropical cyclone in the global model; **a** vorticity at 850 hPa ($\times 10^{-4} \text{ s}^{-1}$); **b** wind speed at 1000 hPa (m s^{-1}); **c** precipitation (mm per 6 hours); **d** specific humidity at 850 hPa (g kg^{-1}) at 14 June 1994 00:00 GMT (Camargo et al. 2007)

upscaled to the GCM resolution (i.e. about 2.8 degrees). This is done by using running average over 5×5 RCM gridpoints. The upscaled precipitation is treated as the large-scale component, and the precipitation difference between the total field and the large-scale component is treated as the local component. There is no local scale component in the GCM simulations. The local scale component accounts for a small portion of total precipitation climatology (e.g. about 15% averaged over Ceará, Brazil). However, it significantly contributes to the total precipitation variability. The standard deviation of the observed local scale component is roughly one-half of that of the observed total precipitation. The RCM has the ability in producing variability of the local component. It can generate about one-half of the observed variations of the local scale component of precipitation in Ceará.

The physical climate anomaly signal in both RCM simulations and observed precipitation data tend to be contaminated by noise, particularly for the local scale component. In order to separate the signal from the noise, both observed and RCM simulated local scale component of precipitation are filtered by retaining only the leading empirical orthogonal function (EOF). Figures 2.5 and 2.6 illustrate the observed and simulated leading EOF patterns, as well as the corresponding principal components, respectively. Compared with the observed leading eigenvector (EOF1), the RCM

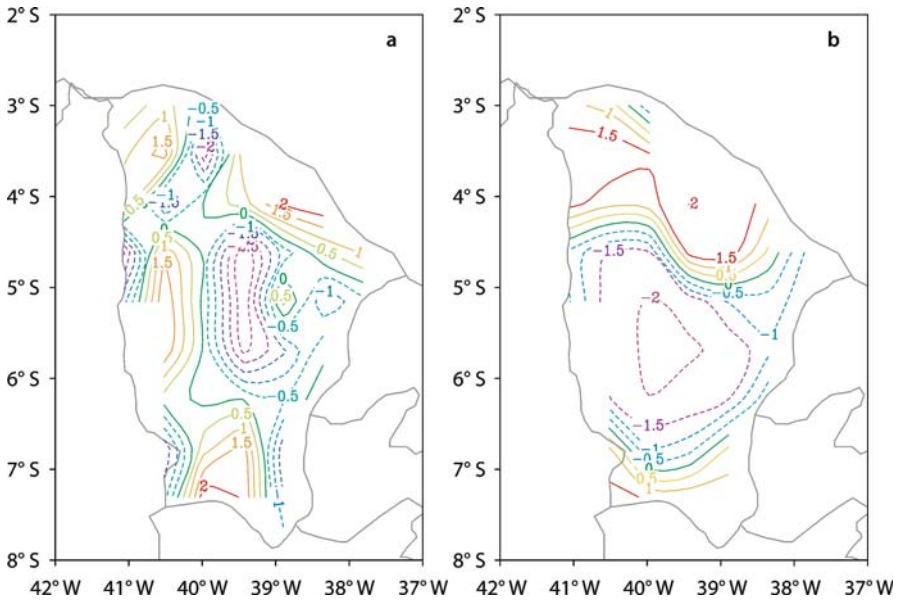


Fig. 2.5. The leading EOF patterns for local scale component of precipitation for the period February–March–April 1971–2000 in Ceará; **a** observation; **b** NCEP RSM simulation. The contours show the actual eigenvector values multiplied by 10. Contour interval is 0.5 (Sun et al. 2005)

captures the general patterns of the observations: positive amplitude along the coastal areas and southern Ceará, and negative amplitude in central Ceará. The leading EOF of the observation explains about 17% of the total variance, while the explained variance for the leading EOF of the RSM is much higher (47%). As shown in Fig. 2.6, the time series of the leading EOF between the observations and RSM simulations are in good agreement, with a correlation coefficient of $r = 0.44$.

Predictability of local scale component can also be revealed by ensemble mean contingency tables. Contingency tables for coastal, central and southern Ceará are given in Table 2.1. They indicate that the regional model has reasonable skill for the local scale rainfall. For instance, it is 5 of 10 years when the RCM indicated below-normal (above-normal) local scale rainfall and the location was observed to receive below-normal (above-normal) local scale rainfall in the coastal Ceará.

An aspect of precipitation variability that is important for climate impact assessments is the distribution of daily precipitation through the season, which can be as important, or even more important, than the seasonal average precipitation. Studies that concern weather analysis in climate models are relatively few. Previous studies indicated errors of too high and too low daily variability of precipitation in GCMs (Mearns et al. 1990). GCMs missed important aspects of the ENSO signal in seasonal statistics of daily precipitation although they are capable of capturing the ENSO signal in seasonal averaged precipitation (Gershunov and Barnett 1998). The analysis of daily precipitation in GCMs is probably of limited value, given the crude horizontal resolution (e.g. the GCM cannot resolve important topographic influences on precipi-

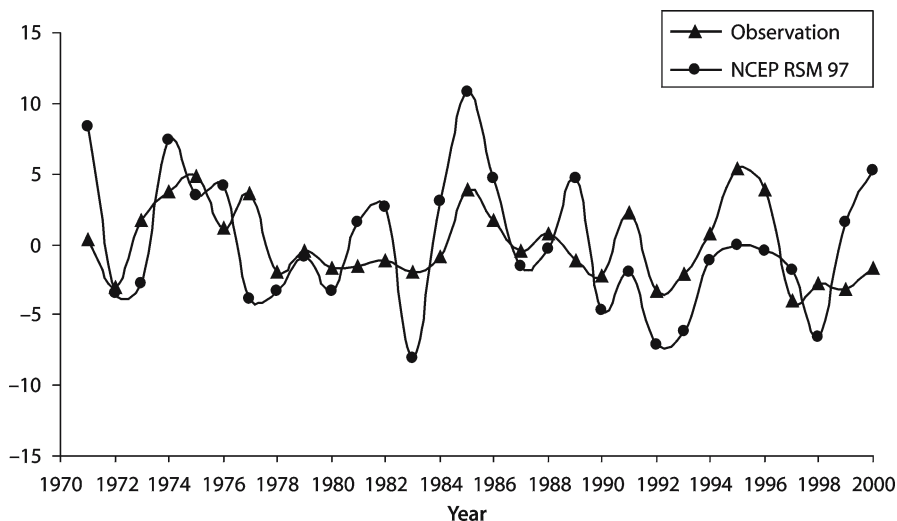


Fig. 2.6. Time series of the leading EOF mode for local scale component of precipitation (Sun et al. 2005)

Table 2.1. Ensemble mean contingency tables for FMA season; **a** coastal Ceará; **b** central Ceará; **c** southern Ceará. Categories of model ensemble mean are listed across rows and observed categories are listed down columns

		OBS			
		Coast	B	N	A
RSM	B	5	3	2	
	N	3	4	3	
	A	2	3	5	

		OBS			
		Central	B	N	A
RSM	B	5	2	3	
	N	4	5	1	
	A	1	3	6	

		OBS			
		Southern	B	N	A
RSM	B	4	3	3	
	N	3	5	2	
	A	3	2	5	

tation, nor synoptic scale precipitation processes) and the crude parameterizations of precipitation. However, the model parameterization schemes are steadily improving, and regional models have relatively fine horizontal resolutions. This mitigates some of the limitations of GCMs, and examination of daily precipitation may prove more fruitful. Over northeast Brazil, the RSM shows reasonable skill in producing the interannual variability of daily precipitation intensity distribution (Sun et al. 2005). The RSM has measurable skill in capturing the variability of dry spells as well. Sun et al. (2007) defined a drought index (D) to measure the severity of drought conditions.

$$D = \sum_{i=1}^n L_i W \quad (2.1)$$

where n is the total number of dry spells during the season, L_i is the length of the i th dry spell in days. A dry spell is defined as three or more consecutive days with daily precipitation of less than 2 mm.

$$W = 1 \quad \text{if } L_i < 10$$

$$W = 5 \quad \text{if } L_i \geq 10$$

The weight (W) is a function of the length of dry spells. Calibration has been done to obtain the optimum values of the weight. A strong weight (W) is given to dry spells longer than 9 days because of the severe damage to crop yields in this region.

The regional model simulates the observed drought index well (Fig. 2.7). Examination of the relationship between the seasonal mean precipitation and the drought index indicates that, (1) the drought index is closely associated with the seasonal mean precipitation only when the drought index is extremely high or low (i.e. the drought index is at least one standard deviation higher or lower than the average), and (2) the drought index is essentially not correlated to the seasonal mean precipitation when the drought index variance is less than one standard deviation. Thus, the drought index can not be derived from the seasonal mean precipitation, and can be treated as an independent variable except for the years with extreme anomalies.

The interannual variability for the drought index is higher than that for the seasonal mean precipitation. The standard deviation-to-mean ratio is 40% (43%) for observed (RCM simulated) seasonal mean precipitation, and 77% (66%) for observed (RCM simulated) drought index. This higher variability provides further evidence of the meaningfulness of the drought index as compared to the seasonal total precipitation.

2.4 Dynamical Downscaling Forecasts

Nested RCMs provide an essential component of the model hierarchy. They enable the predictability of regional climate processes to be studied in much greater spatial detail, and provide a means to make downscaled seasonal climate predictions for appli-

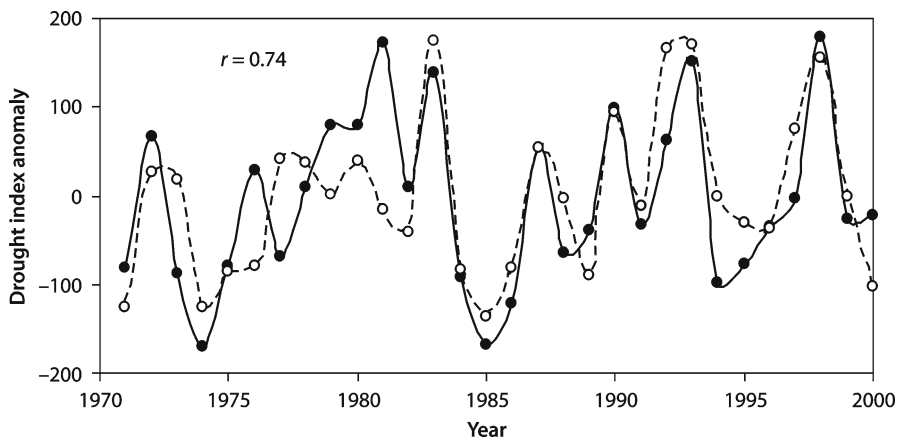


Fig. 2.7. Observed (*solid line*) and RSM simulated (*dashed line*) drought index for the season of February-March-April in the rainfed agriculture region of Ceará. The temporal correlation between them is 0.74 (Sun et al. 2007)

cations. Dynamical downscaling of GCM climate forecasts has been performed in several regions (Diez et al. 2005; Druyan et al. 2002; Fennessy and Shukla 2000; Murphy 1999; Sun et al. 2006; Syktus et al. 2003). Most of them are experimental forecasts. To our knowledge, the first and the only operational climate dynamical downscaling prediction system is the one developed for northeast Brazil (Sun et al. 2006). Operational downscaling forecasts have been issued for northeast Brazil since December 2001. The NCEP RSM with a resolution of 60 km and ECHAM4.5 GCM (T42) are the core of this prediction system. This is a two-tiered prediction system. SST forecasts are produced first, which then serve as the lower boundary condition forcing for the ECHAM4.5 GCM-NCEP RSM nested system.

Two SST scenarios are predicted. The first SST scenario is to persist the observed SST anomalies from the most recently completed calendar month and add them to the observed seasonal cycle. Dynamical predictions using persisted SST anomalies are run only one season into the future. The second SST scenario is the predicted SST anomalies for the upcoming six months. A mix of dynamical and statistical models has been used to construct the SST predictions, varying by tropical ocean basins, and damped persistence with 3 months e-folding time has been used for the extratropical oceans.

Dynamically downscaled forecasts during 2002–2004 have been validated using the ranked probability skill score (RPSS). The overall rainfall forecast skill is positive over a majority of the Nordeste. Forecast skill varies with seasons. The forecast skill is generally higher for March-April-May (MAM) and AMJ seasons than JFM and FMA seasons (Fig. 2.8).

To examine the added value of the RSM forecasts, skill comparison between the downscaled forecasts and the driving global model forecasts was performed. The ECHAM4.5 GCM probability forecasts were generated using the same methods as the

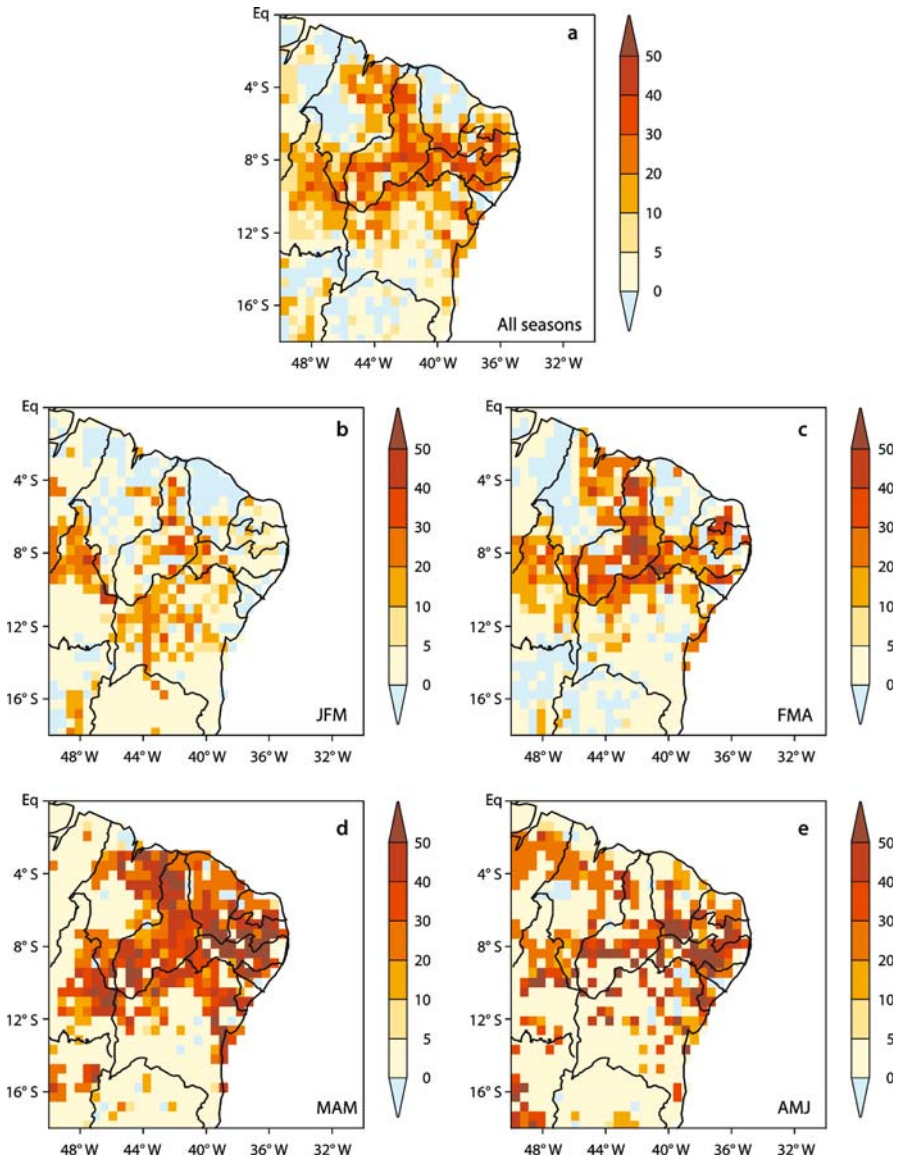


Fig. 2.8. Geographical distributions of RPSS (%) averaged for the one-month lead forecasts during 2002–2004; **a** all season mean; **b** JFM season; **c** FMA season; **d** MAM season; **e** AMJ season

RSM forecasts. The ECHAM4.5 GCM probabilistic forecasts were linearly interpolated onto RSM grids in order to calculate the RPSS using the high-resolution observations. The GCM forecast scores were aggregated for the whole Nordeste. As shown in Table 2.2, the

Table 2.2. Skill comparison between one-month lead RSM forecasts and the driving ECHAM GCM forecasts. The RPSS (%) is aggregated for the Nordeste region

	JFM		FMA		MAM		AMJ	
	ECHAM	RSM	ECHAM	RSM	ECHAM	RSM	ECHAM	RSM
2002	7.1	4.5	5.2	10.1	14.9	23.5	1.2	16.9
2003	-6.1	-3.2	-2.6	7.2	9.4	15.3	5.4	12.2
2004	25.7	-7.4	-0.8	0.4	-5.7	28.6	5.8	18.5

scores of the RSM forecasts are higher than those of the driving GCM forecasts for most seasons, implying that the smaller spatial scale rainfall generated by the RSM is skillful.

Skill scores are based on 12 forecasts. Thus, the results here may be subject to high sampling variability. More reliable skill should be obtained using large forecast samples.

The dynamical downscaling prediction system for northeast Brazil continuously evolves, reflecting continued improvement. A new forecast product, the weather index was issued in January 2005. The weather index uses the daily rainfall time series to measure the severity of drought and flooding conditions. It has been successfully demonstrated that crop yields in the rainfed agriculture region are highly related to the weather index, and the downscaling prediction system is skillful to predict this index (Sun et al. 2007). The NCAR CCM3 and the CSU Regional Atmospheric Modeling System (RAMS) will also be added to this downscaling forecast system, and multi-model ensembling methods will be implemented to consolidate the downscaling forecasts in 2006.

2.5

Future Directions

2.5.1

Improved Model Physics and Parameterizations

Parameterization schemes are based on a spectral gap between the scales being parameterized and those being resolved on the model grid. Therefore, all parameterization schemes are model resolution dependent. However, parameterizations in most regional models are the same as those used in GCMs. These may not be an adequately representation of physics processes in the regional models and may result in incorrect model climatologies and climate drift, which offset the effect of high resolution of the regional model. For instance, the assumption that convective response rapidly to changes in a large-scale, slowly evolving circulation is appropriate for convection parameterizations in GCMs, but it is probably inappropriate for simulations of most mesoscale convective systems in regional models, with 10–50 km grid spacings (Frank and Cohen 1987). Arriving at more general mixing schemes that can cope with the wide range of model resolution is a key problem of relevance to dynamical downscaling.

2.5.2

Land Initialization

Traditionally, the land conditions in regional models are initialized by the driving GCM land conditions using an interpolation scheme. However, the coarse resolution GCM and the fine resolution RCM “see” the land differently due to the heterogeneity of the land surface. This kind of initialization introduces erroneous land surface forcings to the region model. This is as important a limitation on dynamical downscaling as model flaws. The primary problem lies in the land because of the heterogeneity of the land and very limited observations. A major advancement now being proposed is in situ monitoring and generating fine resolution land reanalysis data. Because the land contains the “memory” for time scales longer than a few weeks, land initialization is of fundamental importance in improving dynamical downscaling at seasonal time scale.

2.5.3

Nesting Strategy

For the traditional one-way nesting method, the full large-scale circulation fields from the GCM are provided to the regional model with an interval of 3–12 hours. Errors in the large-scale circulations of the driving GCM are transmitted to the nested RCM, which often results in poor simulations or forecasts of the RCM. For instance, the ECHAM GCM produces a strong divergence bias in the lower troposphere over East Africa. When the traditional nesting method is used, this GCM bias suppresses the convection development in the RCM, and results in a dry bias for the RCM rainfall prediction. To reduce the errors in the driving large-scale fields, an anomaly nesting method has been introduced. This nesting method is based on the premise that systematic errors can be eliminated by replacing the driving GCM climatology with the observed climatology. A case study of dynamical downscaling of seasonal climate over South America reveals that the substantial gains are realized through anomaly nesting (Misra and Kanamitsu 2004). More tests on this method are needed. Reduction of errors in the driving GCM fields can significantly improve the regional model performance.

2.5.4

Downscaling Forecasts – Linking Prediction and Application

Current forecast products generally lack the spatial, temporal and element specificity that users seek for their particular decision-making needs – forecasts are generally made for 3-month seasons, large regions over 1 000 km in width, and mean temperature and precipitation totals only. Dynamical downscaling shows potential to improve climate forecasts towards users’ need. Development of downscaling forecasts system, particularly for developing regions, helps with the design of policies to reduce the climate vulnerability of the most needed populations.

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Development of a Combined Crop and Climate Forecasting System for Seasonal to Decadal Predictions

T. Wheeler · A. Challinor · T. Osborne · J. Slingo

3.1

Rationale

Seasonal and decadal prediction of crop productivity requires simulation of climate and its impact on crops ahead of time. Numerical models can provide such forecasts by using the output from a climate model as input to a crop simulation model. This modeling approach presents a number of challenges that will affect the skill of prediction of the crop forecast. Perhaps the most important of these is: at what scale (both spatial and temporal) should information pass between climate and crop models? This chapter examines this question and other issues concerned with the development of a combined crop and climate forecasting system.

3.2

Numerical Crop and Climate Models

The discipline of crop simulation modeling has advanced rapidly in the last 30 years or so. The complexity of the modeling approach varies from empirical relationships that describe how a few variables affect crop yield, to more process-based equations of some of the underlying chemical and physical processes. Crop simulation models attempt to provide the equations which describe plant physiology and how these processes are affected by genotype, environment and farm management practices. A number of broad types of simulation models have developed. For example, SUCROS and related models (Bouman et al. 1996), the IBSNAT models (Uehara and Tsuji 1993), and the APSIM model (McCown et al. 1996). All these crop simulation models have one thing in common; they require climate information as an input.

Crop simulation models use a rather limited set of climate variables from those output by numerical climate models. Surface temperature is used in the simulation of the rate of crop development, and for the rate of various growth processes such as leaf expansion, photosynthesis and respiration. Calculations of crop water requirements use precipitation and variables that determine evaporative demand such as relative humidity, wind speed and incoming solar radiation. The latter is also required for sub-models of photosynthesis, where these are present. The most common time resolution needed of climate variables is daily, with some crop models requiring diurnal patterns of temperature.

General circulation models (GCMs) are three-dimensional representations of the global atmosphere. Such models simulate the weather and climate over the globe by integrating equations which determine the dynamical flows within the atmosphere and the evolution of its physical state. GCM simulations are often used to understand

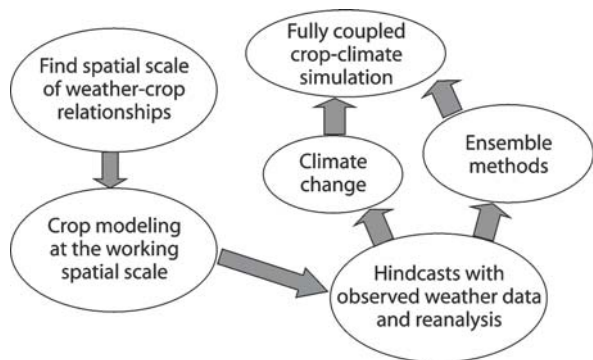
global climate and how it may change under various scenarios, most commonly changing CO₂ concentrations. While GCM output is commonly diagnosed at monthly or yearly timescales, the models actually operate over much shorter time steps in order to resolve the processes which determine the local weather events which go on to define a region's climate. Commonly this time step is less than an hour in order to resolve the diurnal variations in atmospheric variables such as temperature and humidity. Current limitations to computing power restrict the spatial resolution of GCMs to a grid point spacing of approximately 100–200 km. Processes which operate on spatial scales smaller than this (convection, for example) are parameterized.

3.3 Combining Crop and Climate Models

The spatial and temporal scales of numerical climate and crop simulation models are not the same. General circulation models operate on grid sizes of about 200 km, but crop simulation models are designed to use information on climate, soil parameters and management practices at the scale of a field. Crop simulation models operate on daily time-steps and use some seasonal information. GCMs include processes resolved at a range of time-steps, but daily output is not always archived. This mismatch in the spatial and temporal scales of climate model output and crop model input needs to be resolved in order to reduce the uncertainties of seasonal crop forecasts.

A number of approaches to improving the skill of seasonal crop forecasts have been proposed (see review by Hansen et al. 2006). One of these has involved the development of a combined crop and climate forecasting system (Challinor et al. 2003). A number of discrete stages in the development of a combined crop and climate forecasting system have been defined (Fig. 3.1). The first is the definition of the spatial scale of relationships between crop productivity and climate using observations. Crop models that use climate information as input implicitly assume that there is a strong relationship between climate and crop growth, development and yield. Variability in large-scale climate processes such as the Southern Oscillation has been correlated with yields of four crops in Australia (Nicholls 1985) and with maize in Zimbabwe (Cane et al. 1994). Analyses of historical crop data show that the variability in yields due to climate differs with location, from a small climate signal in the temperate UK wheat

Fig. 3.1. The stages of development of a combined crop and climate forecasting systems (redrawn from Challinor et al. 2003)

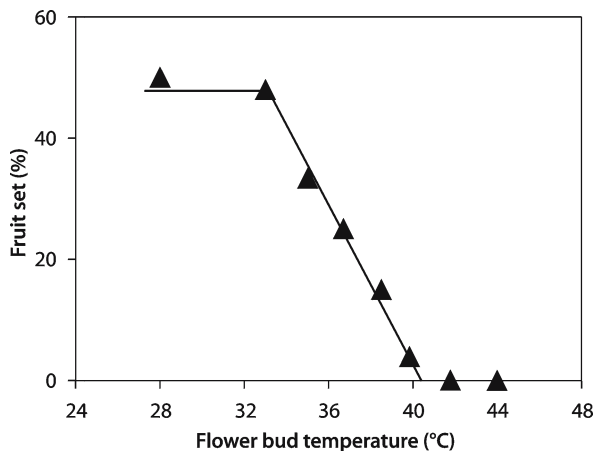


crop (Landau et al. 1998) to more than half the variability of the major crops growing in India attributed to monsoon rainfall (Krishna Kumar 2004). Challinor et al. (2003) examined the spatial scale of the relationship between crops and climate. They found a coherent spatial and temporal pattern between the yield of groundnuts and seasonal rainfall across India for 1966–1990 on the scale of subdivisions (irregular polygons of about 130–480 km). Furthermore, this pattern was closely correlated with the smaller-scale pattern of crop yields at a district level (an average linear scale of 98 km), and with the 850 hPa large-scale circulation pattern. These large-scale correlations between crop productivity and climate therefore established the basis for combining GCM output directly with crop model output in that region (Challinor et al. 2003).

The simulation of crop productivity over a large area needs some simplification of the crop simulation process. A complete set of field-scale inputs will not be readily available over areas of countries and regions, and the grid size will encompass spatial heterogeneity in parameters that describe soils, crop genotype and management practices. Reduced-form crop models (for example, Brooks et al. 2001) and statistical models (such as Landau et al. 2000; Baez-Gonzalez et al. 2005) have been developed, and shown to have predictive skill over large areas. Challinor et al. (2004) sought to maintain a process-based approach in a large area crop model in order to simulate the effects on the crop of short time-step events such as intra-seasonal variability in rainfall, and high temperatures. They proposed a general large area model (GLAM) for annual crops and demonstrated good forecasting skill of the model in a hindcast of the groundnut crop aggregated to all India for 1966–1990.

There is increasing evidence from crop experiments that short-term climate events of only a few days duration can severely impact crop productivity if they coincide with a sensitive phase of crop growth. One example is the occurrence of high temperatures near to the time of crop flowering (Wheeler et al. 2000; Fig. 3.2). The nature of crop response when these climate thresholds are exceeded will be a vital part of the impact of climate change on crop productivity in some regions (Wheeler et al. 1996; Vara Prasad et al. 2002). Therefore, successful prediction of crop productivity by large area crop models on both seasonal and decadal timescales needs robust simulations of the

Fig. 3.2. The effect of a 1-day high temperature event on the fruit/seed set of groundnut plants grown in controlled environments (redrawn from Vara Prasad et al. 2001)



effects of short-term variability in climate on the crop. The high temperature response shown in Fig. 3.2 has been incorporated into GLAM to give a GLAM-HTS (high temperature stress) model version (Challinor et al. 2005c). A similar response of rice to high temperature is also represented in the ORYZA crop model (Matthews et al. 1995). Such models open up opportunities to examine how short-term, sub-seasonal variability in temperature will affect crop productivity.

Rainfall distribution within a growing season can affect crop productivity independent of the seasonal mean. For example, two years with similar rainfall amounts of 394 mm (1975) and 389 mm (1981) during the growing season of groundnut crops in Gujarat, India, are shown in Fig. 3.3. Rainfall in 1975 was evenly spread throughout the season and a yield of 1360 kg ha⁻¹ was attained (Fig. 3.3a). In 1981, there was a break in the monsoon rains during part of the period of grain filling of the crop (55–80 days after planting, Fig. 3.3b). Observed yields were reduced by 34% to 901 kg ha⁻¹. The GLAM crop model simulated a 20% drop in yield in 1981 compared with 1975 (Challinor et al. 2004). Thus, the impact of sub-seasonal variation in rainfall on crop yield was reproduced by the large area crop model.

3.4

Consideration of the Forecast Skill of a Combined Crop-Climate Modeling System

An intermediate step between using climate observations and GCM output for crop forecasting is the use of climate reanalysis data. Reanalysis data are the output of GCMs with weather data assimilated into the climate model. They can be viewed as the most accurate description of the weather at resolutions typical of a GCM, and hence represent an upper limit to the forecast skill of a combined climate/impacts modeling system (Challinor et al. 2003). Challinor et al. (2005a) used the European Centre for Medium Range Weather Forecasting forty-year reanalysis as input to the GLAM crop model run for India. The crop model simulated the correlations between monthly (ERA40) weather and yields in regions where the climate signal was strong. Bias correction of crop yields improved predictions in grid cells in which the sub-seasonal distribution of rainfall in ERA40 was well matched to rainfall observations. However, the skill of crop prediction in areas where ERA40 did not capture either the mean or seasonal cycle in rainfall was poor, even after bias-correction (Challinor et al. 2005a). Thus, the good prediction of sub-seasonal variability in climate by the climate model, and the ability to capture the impacts of sub-seasonal variability in the crop model are both vital to skilful predictions by a combined crop-climate modeling system.

Most crop simulation models are deterministic. That is, one set of model inputs is used to derive a single set of outputs. However, climate on seasonal timescales is inherently unpredictable. The output of multi-model weather ensembles can represent some of the unpredictability and provide probabilistic output (for example, the DEMETER ensembles, Palmer et al. 2004). For crop simulation studies, Challinor et al. (2005b) used output from each of the 63 DEMETER ensemble members as input to the GLAM crop model to simulate the yield of groundnut in western India. The out-

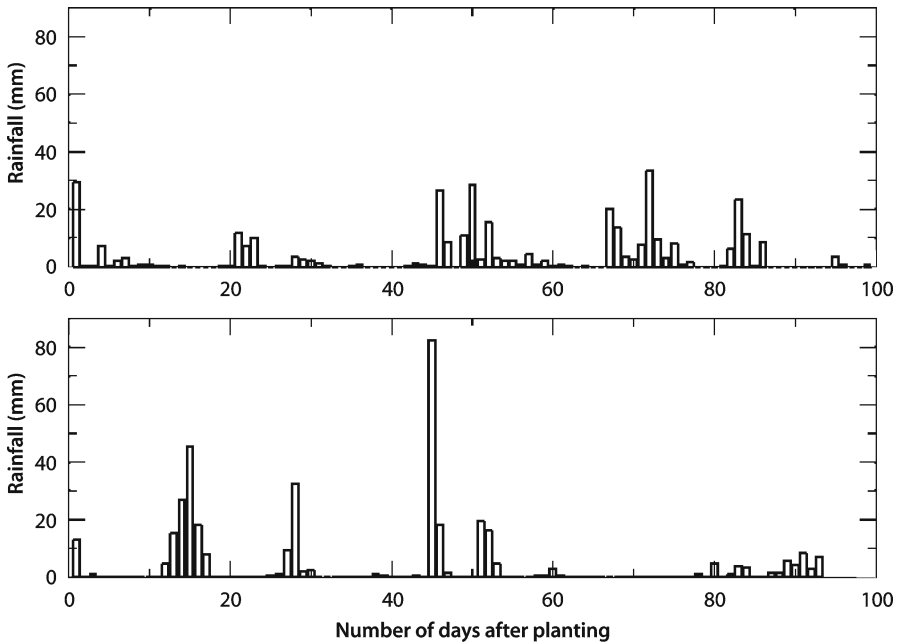


Fig. 3.3. The sub-seasonal distribution of rainfall for 1975 (*top*) and 1981 (*bottom*) in Gujarat, India from the time of sowing of the groundnut crop

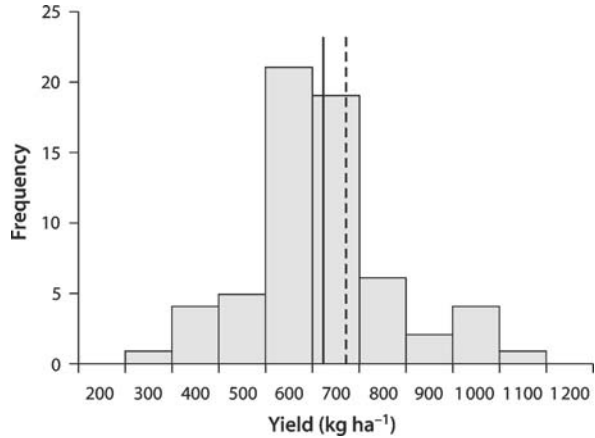
put of the crop model simulations was therefore a probability distribution of crop yields in a single year rather than a single mean value. Considering one year as an example, the mean model prediction for 1998 in Gujarat, India, was 713 kg ha^{-1} . This was close to the observed yield of 773 kg ha^{-1} . However, the crop model output also provides a probability distribution about this mean, from which it is clear that there was a non-zero probability of very good and very poor yields in the seasonal crop forecast (Fig. 3.4). The probabilistic hindcasts showed good skill in the prediction of crop failure (defined as a yield threshold of, for example, 400 kg ha^{-1} , Challinor et al. 2005b). Cantelaube and Terres (2005) produced probabilistic forecasts of wheat yields in Europe using the output of the DEMETER ensembles with the WOFOST crop model. They concluded that reliable predictions of yield could be obtained earlier in the season with the DEMETER forecasts compared with a current operational system. Thus, there seems to be a lot of potential for the probabilistic forecasting of crop yields.

3.5

An Integrated Approach to Climate-Crop Modeling

The traditional approach to crop simulation has used a one-way flow of information from climate model output to crop model input. However, it is increasingly recognized

Fig. 3.4. Probabilistic crop yield forecast using the DEMETER multi-model ensemble for the groundnut crop grown in Gujarat, India in 1998. The *solid* and *dashed vertical lines* are the model average and observed yield, respectively



that land surface vegetation affects climate (for example, Cox et al. 1999; Pitman et al. 1993; Osborne et al. 2004). Crops comprise about 12% of the land surface vegetation (Ramankutty and Foley 1998). They can modify their own environment through the water cycle and surface temperatures. Therefore, decadal forecasts of crop productivity used in climate change impact assessments may need to consider the interaction of crops and climate over these longer timescales. This can be achieved by integrating the biological and physical modeling through working on common spatial scales and fully coupling crop and climate models.

Crop growth and development routines from GLAM were incorporated into the land surface scheme of a GCM (Osborne et al. 2005). In the new crop-climate model, crops grow in accordance with the simulated environment (soil and atmospheric states) of the climate model while at the same time altering the land surface characteristics important for the determination of surface energy balance such as albedo and surface roughness (Fig. 3.5). When forced with observed variations in sea surface temperature, the coupled model's crop growing seasons and final yields were in good agreement with observations. However, the ability of the model to accurately recreate observed crop production is closely linked to the ability of the climate model to recreate observed weather and climate patterns.

Coupling a crop model to a GCM may potentially reduce the uncertainty of crop simulations by capturing the effect of cropped areas on climate and through using GCM output directly. However, it is difficult to precisely test the effects of coupling a crop model to a GCM because the coupled (online) and separate (offline) models cannot easily be run in a comparable manner. Nevertheless, we attempted a preliminary comparison of crop yield simulations by on- and offline crop models. The yield of groundnut crops across India (30 grid cells) was simulated for 1979–1989 using GLAM (offline; Challinor et al. 2004) and GLAM-MOSES (online; Osborne et al. 2007) and the output compared with observed yields. For this, the on- and offline runs were designed to be as similar to each other as possible. However, it is important to note that there were still some differences in model data inputs and model set-up that are characteristic of the two different approaches and so were not altered (Table 3.1). So, our comparison

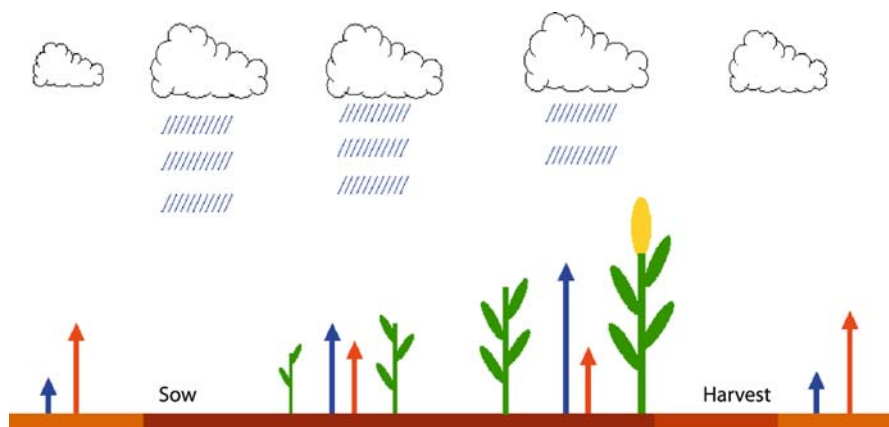


Fig. 3.5. Schematic illustration of the simultaneous coupling of the atmospheric state, precipitation, soil moisture content, crop growth and surface fluxes within the crop-climate model of Osborne et al. (2007). Blue and red arrows represent latent and sensible heat fluxes, respectively

Table 3.1. Summary of the differences between the on- and offline simulations of groundnut yield across India

	Offline GLAM ^a	Online GLAM-MOSES ^g
Weather data	IITM and CRU datasets ^b	HadAM3
Soil data	FAO dataset ^c	HadAM3
PET and T ^d	Calculated within GLAM	Calculated from MOSES ^e
Time-steps of VPD and THT ^f	Daily	Diurnal cycle resolved
Yield gap parameter ^g	Varied spatially	0.5
Growing areas	Prescribed from observed	From crop mask ^h

^a General Large Area Model crop model (Challinor et al. 2004).

^b Indian Institute for Tropical Meteorology and Climatic Research Unit.

^c Food and Agriculture Organisation of the UN.

^d Potential evapotranspiration and crop transpiration.

^e Met Office Surface Exchange Scheme (Cox et al. 1999).

^f Vapour pressure deficit and thermal time for crop development.

^g Reflects how farm yields compare with potential crop yields.

^h See Osborne et al. (2007).

comprises the effect of coupling crop growth to the atmosphere and the differences shown in Table 3.1.

The hindcast by the online model simulated the interannual variability in the observations reasonably well (Fig. 3.6a), in accordance with the longer time series hindcast reported by Challinor et al. (2004). The mean yield predicted by the online crop model was less (on average by 17%) than the offline model. The variability in the

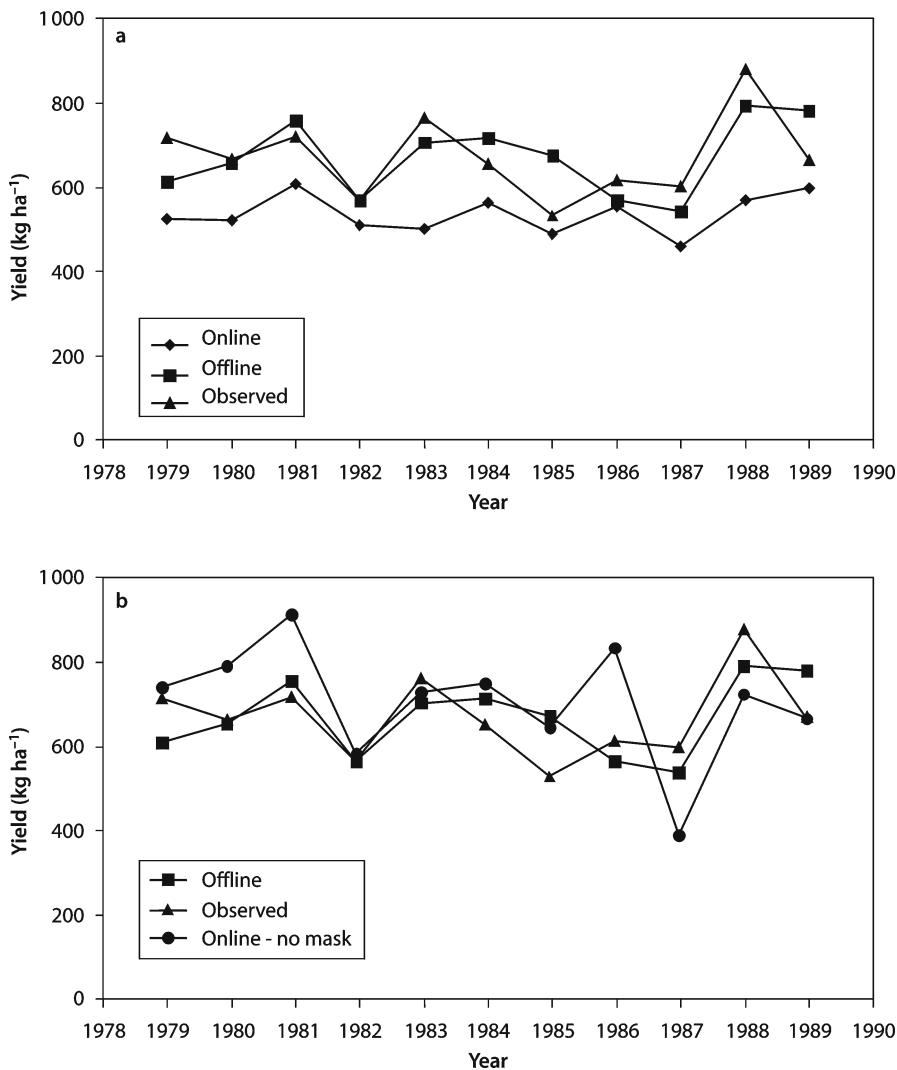


Fig. 3.6. Hindcast of groundnut yields across India; **a** from the on- and offline crop models; **b** from the online model without the crop mask and offline crop model. Observations are from national yield statistics of India

online simulations was similar to that in the observed data, with the exception of the high observed yield in 1988 which was not captured. A further hindcast by the online model was generated by removing those grid cells excluded by the crop mask (but where in reality there was some groundnut grown) from the calculation of the all-India weighted mean yield. This change brought the mean response simulated by the online model much closer to the offline simulations and the observations, and reproduced the high yield of 1988 (Fig. 3.6b).

3.6

Conclusions

Successful seasonal and decadal prediction of crop productivity requires skilful forecasts of climate and its impacts on crops. One approach is to combine climate and crop modeling at a common, large scale in order to exploit crop-climate relationships that are observed at a scale close to that of GCM output. Such a combined climate-crop modeling system provided hindcasts of country-scale crop yields with reasonable forecast skill. Furthermore, the combined modeling system allowed the use of climate re-analysis and probabilistic GCM output in crop productivity applications. Such research is now leading to a fully coupled crop-climate model that captures the two-way interactions between crops and climate. The use of large area crop simulation models both on- and offline with numerical climate models should aid progress towards improved seasonal and decadal forecasts of crop productivity.

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Delivering Climate Forecast Products to Farmers: *Ex Post* Assessment of Impacts of Climate Information on Corn Production Systems in Isabela, Philippines

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4.1 Introduction

Corn production is the principal source of family income for about 24 million Filipinos. Isabela Province, located in one of the most depressed regions in northern Philippines, is considered the top corn-producing province in the country contributing 17% or 536 353 tons of the total yellow corn production in the country. Corn is grown rainfed in Isabela. Monocropping of corn is predominantly practiced in Isabela and there are two cropping seasons per year – wet season cropping from May to August and dry season cropping from November to February. In 2003, a total of 146 965 hectares were planted to yellow corn in the province. In the same year, average yield of yellow corn was 3.65 tons per hectare (t ha^{-1}) which was comparatively higher than the national yellow corn yield average of 3.03 t ha^{-1} . Most of the corn type being produced in the province is yellow corn which comprised 95% of the total corn produced in the province (Lansigan et al. 2001). Yellow corn is primarily used as animal feed ingredient especially for poultry and swine.

Climate in the agricultural region of Isabela has historically no pronounced dry or wet seasons – relatively dry in the first half of the year and wet during the second half. Average rainfall is 1 844 mm per year, mean temperature is 29°C and mean relative humidity is 66%. In general, the climate in the vast plains of Isabela is suitable to corn production. However, in 1998, drought devastated 110 996 hectares of corn field in Isabela incurring a production loss of about 219 000 metric tons of corn (BAS 2001). The Philippines is visited by an average of 20 typhoons per year from 1948 to 2000 (PAGASA 2001). The months of July, August, and September have the most frequent typhoon occurrence in the country (Kintanar 1984). Experts have observed that typhoon development in the Philippines has been erratic and almost unpredictable with strongly varying movement and structure (Tacio 2000).

In recent years, improvements in our understanding of the interactions between the atmosphere and its underlying sea and land surfaces, advances in modeling the global climate system, and the substantial investment in monitoring the tropical oceans helped provide a degree of predictability of climate fluctuations at a seasonal lead time in many parts of the world (Hansen 2002). This has allowed critical agricultural decisions to be made in crop production to minimize negative impacts of, or maximize the benefits from the expected climatic conditions (Gadgil et al. 2002). Thus, this chapter seeks to examine the agronomic and economic impacts of advanced climate information on corn production systems in Isabela Province, Philippines as affected by planting date decision.

4.2 Methods

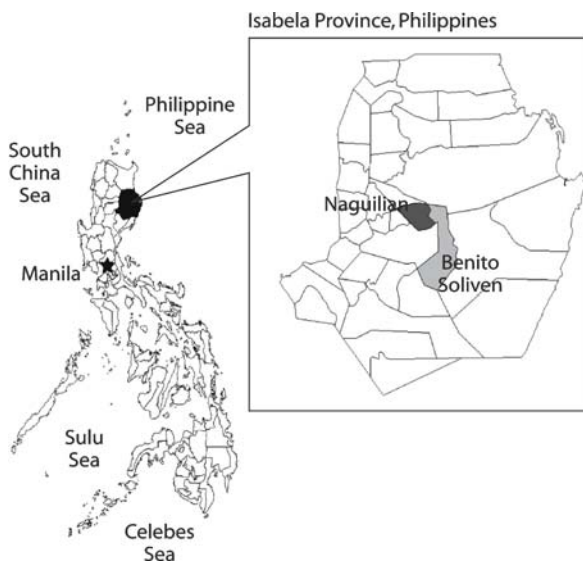
4.2.1 Determining Planting Dates Recommendation for Corn Farmers in Isabela, Philippines

As part of the objective of the case study, crop performance and yields obtained using two planting dates were compared to demonstrate the importance of using the climate forecast, i.e. planting date determined and rationalized by considering the advanced seasonal climate information versus the farmer's choice of planting date. Analysis of seasonal climate forecasts and the use of the historical data on normal precipitation alone suggested that the planting date could not be determined exactly. Thus, an alternative practical approach was to use the available historical rainfall data combined with statistical analysis to determine the distribution of the end of rainfall occurrence and to validate the planting date using crop simulation. The 42-year monthly rainfall data of Isabela were classified into El Niño, La Niña or neutral years leading to the classification of the October 2003–January 2004 corn cropping season as El Niño, La Niña or as neutral season. The historical end of the rainfall occurrence for the October–January cropping season for the grouped years was also determined. Planting date was determined such that the critical stage of corn growth should be synchronized with the period when there is adequate soil moisture so that crop yield will not be significantly affected or reduced. It has been reported that water stress or moisture deficit from tasseling/reproductive stage to maturity is the most critical stage of corn growth which significantly reduced corn yield (Shaw and Thom 1951; Coligado et al. 1963; Papadakis 1966; Classen and Shaw 1970; and Sys et al. 1993). This critical period is about 55 days after planting. Thus, the recommended planting date was obtained by determining the date such that the critical crop growth stage will not coincide with the period of moisture stress (i.e. about 55 days before end of rainfall occurrence). For both Naguilian and Benito Soliven, the recommended planting date is 21 October 2003. However, planting date for Benito Soliven was moved to 27 October 2003 due to technical tribulations. Unlike in Naguilian, farmers in Benito Soliven prepare their land manually (i.e. using animal-drawn plow) that requires longer number of days. Tractors are not used in this area due to its rolling terrain. Each planting date was further validated to be optimal for each site by crop simulation modeling using CERES-Maize model by simulating crop yields with the specified dates of planting as model input data.

4.2.2 Field Implementation

Six (6) corn farmers with a farm size of at least two hectares each were selected as case study cooperators. Three (3) farm sites were established in different villages/communities in the town of Benito Soliven. The municipality of Benito Soliven is located at 16°55' N longitude and 121°60' E latitude. It is about 98 meters above sea level (Fig. 4.1). Corn in this area is produced on rolling terrain and being located in an elevated area compared to the rest of the corn production sites in the province, Benito Soliven's climate-related concern is mainly drought occurrence.

Fig. 4.1. Location of the municipalities of Naguilian and Benito Soliven in Isabela Province, Philippines



The other three (3) farm sites are located in different communities/villages in the town of Naguilian, Isabela Province. Naguilian is located at 17°60' N longitude and 121°50' E latitude. It is about 38 meters above sea level. Naguilian is situated along the Cagayan River, the biggest river system in northern Philippines. The town's major weather-related concern is flood occurrence.

Each of the farms identified was divided into two main plots with timing of planting as the treatment, and each experimental unit measuring 2 500 m² with two replications. One plot was planted based upon the recommended planting period derived from the use of climate forecast products combined with the use of statistical analysis of long-term historical weather data of the province. The other plot was planted based on the farmer's choice of planting date. Most corn farmers in Isabela province base their choice of planting dates on the actions of neighboring farmer leaders in the vicinity. Plots owned by same farmer (i.e. with different planting dates) were managed by the same farmer employing similar cultural practices. This was closely monitored by the project staff who lived in the area.

The choice of planting date is the sole recommended modification from established farmer's practice. Since the experimental cropping season is towards the dry season, the main consideration in the choice of planting date is the assurance of moisture availability during the tasseling or reproductive stage in corn production. In the tropics, this is approximately 55 days after planting.

4.2.3

Data Gathering

The case study throughout the cropping season was closely monitored and farm activities were duly recorded to control possible sources of variation other than the planting dates. Yield and income generated were determined at harvest time. Actual farmer's income based on the prevailing price of corn during harvest time was also determined.

4.3 Results

4.3.1

Farmers-Cooperators' Background

Naguilian Farmer No. 1: Mr. Arturo Marfil is 52 years old, has reached collegiate-level of education and has four hectares of farm land solely devoted to corn. He obtains 40% of his farm capital from private lenders/traders. He owns a hand tractor and corn sheller which facilitate easier land preparation and shelling. On the side, Mr. Marfil raises poultry, swine, cattle and freshwater fish to supplement his farm income.

Naguilian Farmer No. 2: Mr. Felipe Ignacio, Jr. is 49 years old, has reached high school-level education and has 28 years of corn farming experience. He grows corn on three and half out of his four hectares of farm land. His wife also assists in his farming activities. He derives 90% of his farm capital from private lenders/traders.

Naguilian Farmer No. 3: Mrs. Herminia Accad is 64 years old and a retired elementary school teacher. She has 20 years of farming experience. She solely manages her 2.3 hectares of corn farm and hires local farm hands to perform the necessary field operations. She derives about 30% of her farm capital from local lenders/traders.

Benito Soliven Farmer No. 1: Mr. Miguelito Santos is 44 years old, has an agricultural engineering degree from a local university and has 24 years of corn farming experience. Mr. Santos works for the local government and hires local farm workers to do the day-to-day farm operations. Mr. Santos allocates 2 hectares out of his 4 hectares of farm land to corn production. He obtains 20% of his farm capital needs from private lenders/traders. He traditionally plants corn in November for the dry season cropping and May for the wet season cropping.

Benito Soliven Farmer No. 2: Mr. Edmund Gauran is 27 years old, has a university degree and also works for the local government. Just like Mr. Santos, Mr. Gauran obtains 20% of his farming capital from private lenders/traders. He hires local farm workers to till his 2 hectares of corn plantation.

Benito Soliven Farmer No. 3: Mrs. Esmenia Aquino is 65 years old and has 35 years of corn farming experience. She completed elementary education. Mrs. Aquino owns seven hectares of farm land and allots four hectares of her property to corn production. She also hires local farm workers for her crop operations. Corn production is her primary source of income. She utilizes her own funds to finance her farm operations.

4.3.2

Corn Yields

The choice of planting date is an important decision especially in rainfed, annual crop production system like corn. The planting period, which lasts 30–90 days according to climatic zone and date of onset of rains, is the most critical part of the farming sea-

son (Ingram et al. 2002). The difference in planting date during this study ranged from 3 days to 39 days (Table 4.1). The yield and income variation based on differences in planting date are shown in Figs. 4.2 and 4.3. There is an appreciable difference in the levels of corn yields and farm net income in the two sites with distinctly different elevations and agro-environment. Overall, crop yields in the low elevation, flood-prone corn areas in Naguilian are relatively higher than those in the high-elevation, drought-prone corn areas of Benito Soliven.

As shown in Fig. 4.2, the yield in corn areas that followed a planting date based on climate forecast was higher in five out of six farms that participated in the study. This overall yield advantage is about 18% compared to farms with planting dates based on farmer's choice. In the lower elevation areas of Naguilian, areas with planting date based on climate forecast have 11% better yield compared to areas planted following farmer's choice of planting date. Yield in areas that utilized advanced climate information was 25% higher than the overall community yields average. The general trend was similar in the higher elevation and drought-prone municipality of Benito Soliven. Climate forecast-based planting resulted to 12% better yield than areas planted based on individual farmer's choices and 13% better yield than the general community yield average. For Mrs. Herminia Accad (Farmer No. 3) in Naguilian, Isabela, a difference of three days in the choice of planting date resulted to a decrease in yield by 13% or about 770 kilograms of corn yield per hectare.

4.3.3

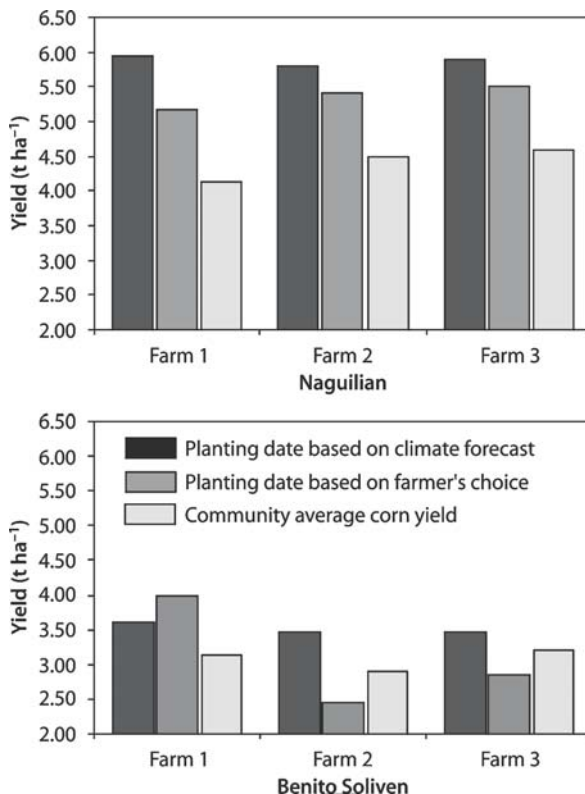
Income from Corn Production

In terms of farm income, areas in Naguilian that utilized advanced climate information have 18% more income on a per hectare basis compared to farms that depended on individual farmer's choice of planting dates (Fig. 4.3). Income differences based on choice of planting dates ranged from 7.2 to 27% in Naguilian, Isabela. In Benito Soliven, the income advantage resulting from the application of the recommended planting dates based on climate forecast was about 32% on a per hectare basis. Income differences of participating Benito Soliven farmers ranged from 4.3 to 65.7%. The huge 65.7%

Table 4.1. Planting dates based on climate forecast products and farmers' choice of dates of planting corn in Isabela Province, Philippines

Location – cooperator	Planting date	
	Based on climate forecast	Based on farmer's choice
B. Soliven – Farmer 1	27 October 2003	18 November 2003
B. Soliven – Farmer 2	27 October 2003	10 October 2003
B. Soliven – Farmer 3	27 October 2003	18 October 2003
Naguilian – Farmer 1	21 October 2003	17 November 2003
Naguilian – Farmer 2	21 October 2003	30 November 2003
Naguilian – Farmer 3	21 October 2003	24 October 2003

Fig. 4.2. Corn yields at Naguilian and Benito Soliven, Isabela, Philippines as affected by planting dates

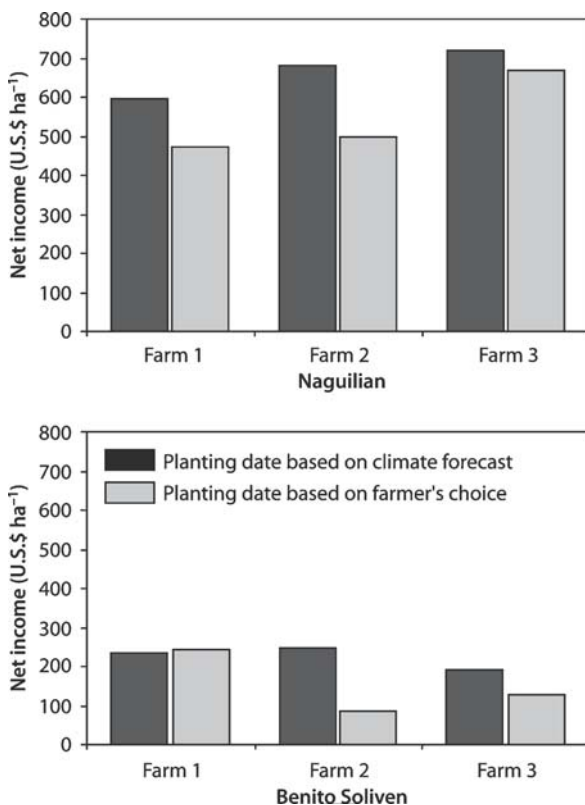


difference in the per hectare income of Mr. Edmund Gauran (Farmer No. 2) of Benito Soliven was brought about by the 29.4% yield advantage and the better price of corn grains when the harvest from area planted using climate forecast was sold in the local trading center.

4.4 Conclusions

For rainfed corn production systems in Isabela, Philippines, the recommended planting date for the location can be estimated by determining the historical end of the rainfall occurrence based on available climate data, and deducting from this period about 55 days to avoid water stress during the critical period of the reproductive stage from flowering until the end of grain formation. During wet season cropping, however, the use of advanced climate information to determine the recommended planting date may not be useful and practical as the crop will not experience significant water stress throughout its growing period since there is adequate soil moisture available. This excludes the fact that the wet season is also characterized by atmospheric disturbances due to typhoons with strong winds and heavy rainfall which may destroy the crops.

Fig. 4.3. Net income of corn farmers in Naguilian and Benito Soliven, Isabela, Philippines as affected by planting dates



Field research results have demonstrated that corn farms which used climate information to base the planting date obtained higher crop yields and higher net income compared to areas which were planted based on farmers' decision of planting date. Farms which used advanced climate information-based planting date had a generally higher yield than the average level in the entire village. These results had shown that using advanced climate information in farm-level climate-related decisions in corn production system can lead to increased yield and farm income and can minimize risks due to climate variability.

Acknowledgements

The research leading to this case study was supported by the International Research Institute for Climate Prediction (IRI; <http://iri.columbia.edu>), Global Change System for Analysis, Research and Training (START; www.start.org), the David and Lucille Packard Foundation, and the Philippine National Corn RDE Program.

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Seasonal Predictions and Monitoring for Sahel Region

G. Maracchi · V. Capecchi · A. Crisci · F. Piani

5.1 Introduction

Although seasonal forecast applications are still in an early stage of development there is now enough collective experience from research efforts around the world to induce some meaningful considerations.

In particular, for West Africa, whose economy is mainly dependent on agricultural sector, the possibility of having seasonal predictions for farm level and food early warning system applications is very useful. Due in part to its interdisciplinary nature, the literature on agricultural applications of seasonal forecasts is scattered. A few collected works (Sivakumar 2000; IRI 2000) cover efforts across countries.

Concerning meteorological seasonal predictions in the following pages, some of the main methods and data over the world are summarized:

- At the Hadley Centre of UK Met Office outlooks for temperature and rainfall up to 6 months ahead for all regions of the globe, updated shortly after the middle of each month are available. These forecasts are based on an empirical model using multiple linear regression (MLR) and linear discriminant analysis (LDA) and using as input sea surface temperature anomalies (SSTAs) representing interhemispheric contrast, and tropical Atlantic and El Niño-Southern Oscillation (ENSO) signals (Folland et al. 1991).
- At the Climate Prediction Center (CPC) at NCEP a canonical correlation analysis is conducted for the African continent using quasi-global SST data for the area 40° S to 60° N (Barnston et al. 1996).
- At the Prediction Group of the Colorado State University an empirical method is developed using as inputs previous Sahel precipitation, tropical North and South Atlantic SSTs, Pacific SSTs and Quasi-Biennial Oscillation (QBO) (Landsea et al. 1993).

Concerning Numerical methods, studies are going on at the following centers:

- United Kingdom Met Office: an ensemble of runs by UKMO's Third Generation Coupled Ocean-Atmosphere GCM (HadAM3) are used with forced SSTAs assumed to be persistent through the forecast period.
- European Centre for Medium-Range Weather Forecasting (ECMWF): a fully coupled ocean-atmosphere model produces global predictions each month for precipitation and rainfall. Atmospheric and land surface conditions come from ECMWF operational systems. Other oceanic thermal input data come from established observation networks (Stockdale et al. 1998).

- International Research Institute for Climate Prediction (IRI) at Columbia University: a multi-ensemble approach using different AGCMs generates global forecasts; Pacific SSTA forecast (from the NCEP model) and other SSTAs from statistical techniques are used. Much information can be found at <http://iri.ltdgo.columbia.edu/climate/forecast/>.

Obviously skills for these long-range predictions are substantially lower than for the more familiar shorter-range predictions; predictive skill and detailed comparisons between the numerical methods and statistical ones are rare (Goddard et al. 2001). For West Africa, the seasonal rainfall forecasting skill of statistical methods (in particular the Climate Prediction Center method using CCA) is notable (CLIVAR 1998) and is largely due to the persistence of successive rainfall anomalies.

Anyway Goddard et al. (2001) point out that different techniques have different performances according to the region of interest and that end user interactions play a part. For this reason, regional climate outlook forums are needed to keep in touch policy makers, funding agencies, and users of climate information. Basically the role of climate forum is to discuss the current state of the global and regional climate, to produce a consensus seasonal forecast in the region in question and to develop a mitigation plan based on the seasonal outlook.

5.2

Data and Methods

The choice of the Institute of Biometeorology for the seasonal predictions is an analogue statistical approach for aggregated monthly rainfall precipitation in the Sahel region on the basis of “similarity” conditions of the sea surface temperature in three areas in the world defined as: Niño 3 (5°S – 5°N ; 150°W – 90°W), Guinea Gulf (10°S – 5°N ; 20°W – 10°E) and Indian Ocean (5°S – 15°N ; 60°E – 90°E). Areas chosen for the study are shown in Fig. 5.1.

The theoretical analysis of the method and the justification of the predictors can be found in the work of Vizzy and Cook (2001) where the sensitivity of precipitation over West Africa is studied using a GCM and in the work of Giannini et al. (2003) who presented the evidence that Sahel rainfall interannual variability is due to the response of the West African monsoon to oceanic forcing and is amplified by land-atmosphere interactions.

In the analogue method each month of every year of the time series taken into account is characterized by six variables: three sea surface temperature standardized anomalies (SSTAs) and their respective tendencies (namely “change rates”, CRs); the SST values come from the Reynolds dataset used to feed NCEP/NCAR models (Reynolds and Smith 1994). In computing the SSTAs the standardization is obtained from the current SST values through subtraction of the 1979–2003 SST average and division by 1979–2003 SST standard deviation (the so called z-score); the CRs are defined as the difference between the standardized current SSTAs and those of the previous month. Then the method is based on the minimization of the Euclidean distance between the esa-vectors defining each month of the time series to find the most similar year (namely analogue) and assign the values observed in the analogue year to the forecast rainfall field. In formula we find:

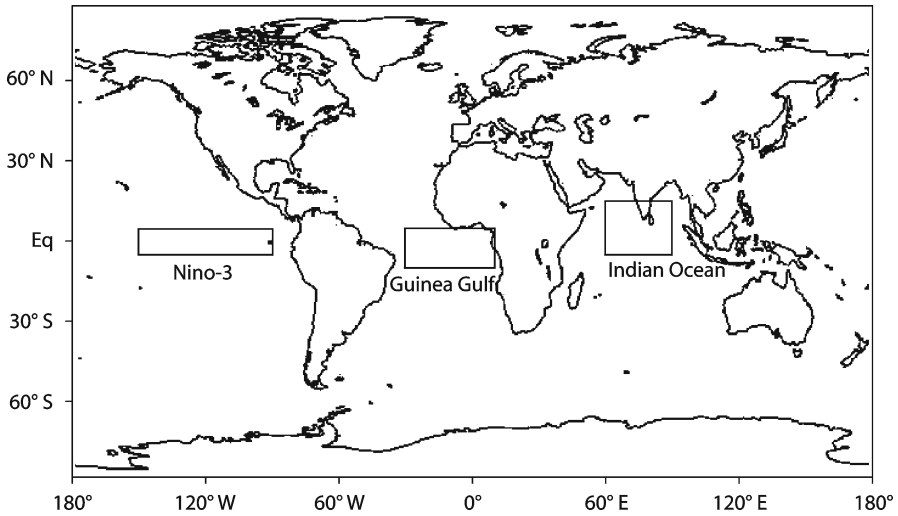


Fig. 5.1. Areas chosen for the computation of SSTAs and CRs (see text for definition)

$$\min \sqrt{\left(\sum_1^6 (P_{\text{curr}}^i - P_{\text{past}}^i)^2 \right)}$$

where each P^i is chosen in the domain of the predictors.

Once the best analogue year is found the precipitation anomaly, absolute values and in percentage, are then computed, compared with the 1979–2003 climatological mean; the dataset used is the Global Precipitation Climatology Project (Xie et al. 2003).

5.3 Results

The method became operative in the summer of 2004 and at the moment trials are ongoing for the hindcast of rainy seasons in Sahel for the period 1979–2003. Due to the specific dynamical behavior of the West African monsoon this simple analogue characterization is able to catch main features of rainfall precipitation patterns during the summer period. The validation of the model, through analysis of forecast skills in terms of probability of detection (POD) and false alarm rate (FAR) in predicting years above and below the normal, shows encouraging results. The operative result of seasonal predictions at the Institute of Biometeorology is issued, on the dedicated website http://www.ibimet.cnr.it/Case/sahel/products_01.php, every month and the temporal validity is for the following three months.

In semi-arid tropical climates with clear wet and dry seasons and pronounced interannual variability such as in the Sahel, the date of the start of the wet season, the onset, is a critical factor in deciding when to plant crops. Reliable information on the

onset of the rainy season, one month or more ahead, would be very helpful for farmers and decision-makers. Many studies have been carried out on the start of wet season in climatological studies of the average start date, but few attempts have been made to make a seasonal forecast of the start of the current rainy season. One of the most recent technique, among the others, to estimate the start and the cessation of the rainy season in West Africa using surface data is proposed by Omotosho (1992) and Omotosho et al. (2000).

According to Sultan and Janicot (2001), the dynamics of the West African monsoon is divided in two phases: the preonset and the onset. The former occurs in late spring when the Intertropical Convergence Zone (ITCZ) establishes itself at 5° N, climatologically at 14 May and the latter occurs when the ITCZ abruptly shifts northward, climatologically at 24 June. So the ITCZ moves from 5 to 10° N, where it stays for the whole month of August and this is when the rainfall declines in the Guinea Gulf and increases in the South Sahel.

For the identification of the rainy season's onset the Institute of Biometeorology has followed and developed the idea first proposed by Fasullo and Webster (2003) concerning the identification of the start and end of the rainy season in India due to the Indian monsoon dynamics. Basically the method takes into account the vertical integrated moisture transport, say *VIMT*, defined as:

$$VIMT = \int_{850 \text{ mb}}^{1000 \text{ mb} \cong \text{surface}} qU \frac{dp}{g}$$

where q is the specific humidity in units of g kg^{-1} , U is the wind vector in units of m s^{-1} , p is the pressure in units of mb, and g is the gravitational acceleration in units of m s^{-2} .

The dataset used is the NCEP/DOE-reanalysis2 (Kalnay et al. 1996). The vertical integral is limited to the first 1500 meters (up to 850 mb level) since during the rainy season and in the area of interest most of the moisture is confined below this level as shown in Fig. 5.2 (zonally averaged).

Following Fasullo and Webster (2003), the time series X of *VIMT* in the area of interest is normalized by the climatological annual cycle through the transformation:

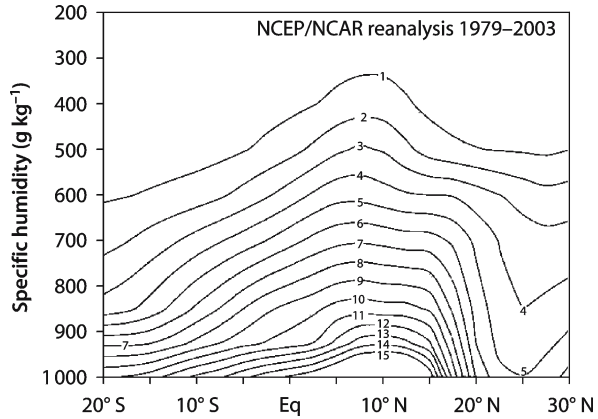
$$\bar{X} = 2 \left(\frac{(X - \min(\chi))}{(\max(\chi) - \min(\chi))} \right) - 1$$

where \bar{X} is the normalized time series (1979 → 2002) and χ are the values of the climatological annual cycle.

The so constructed monsoonal index *HOWI* (Hydrological Onset and Withdrawal Index) is based on the hydrological cycle and is

- associated with the establishment of the large-scale processes that drive the monsoon circulation,
- relatively insensitive to individual synoptic disturbance and bogus monsoon onset,

Fig. 5.2. Specific humidity latitude/height profile for the period July-August-September averaged over the longitude = (-10° , 10°)



- based on fields that experience large and rapid variability during the monsoon onset and withdrawal,
- based on fields that have been well observed over an extended period.

Because the index is normalized, we can evaluate the definition that the time of the year when the index exceeds and falls below, respectively, the fixed threshold of 0, marks the pre-onset of the rainy season and the retreat of monsoon. For the pre-onset the constraint imposed is that the *HOWI* must increase at least during the five days prior to when it exceeds 0 and for the withdrawal the constraint is that the *HOWI* must be lower than the threshold 0 for the following ten days.

Normalizing the rain using the GPCP dataset we can see evidence that the date identified via *HOWI* method anticipates the rain onset (when normalized rain exceeds $\frac{1}{2}$ of its climatological value) of about 7 weeks in the southern part of West Africa and of about 6 weeks in the Sahel region (latitude = 10° – 15° N, longitude = 10° W– 10° E). In general the time lag between the pre-onset of *HOWI* and the onset of rain decreases with increasing latitude and it makes the *HOWI* a valuable predictor for the onset on the monsoon season. Since the withdrawal of the monsoon is more rapid than the onset, the time lag between the date in which *HOWI* < 0 and the normalized rain $< \frac{1}{2}$ is close to zero. The joint dynamics of climatological *HOWI* and climatological normalized rain profile in the Sahel region and in North Sahel region (latitude = 15° – 20° N, longitude = 10° W– 10° E) is illustrated in Figs. 5.3 and 5.4.

Table 5.1 below shows a summary of the predictive power and use of the *HOWI* index in West African monsoon area (latitude = 5° – 20° N, longitude = 10° W– 10° E), Sahel region and North Sahel region.

5.4 Conclusions

It seems clear that the skill of seasonal forecasting methods could be enhanced by the provision of improved input data and, improved model of interactions between

Fig. 5.3. Joint behavior of *HOWI* profile and normalized rain profile in Sahel region

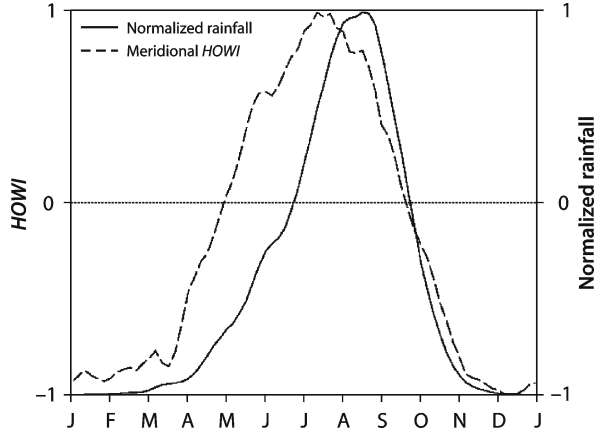


Fig. 5.4. Joint behavior of *HOWI* profile and normalized rain profile in North Sahel region

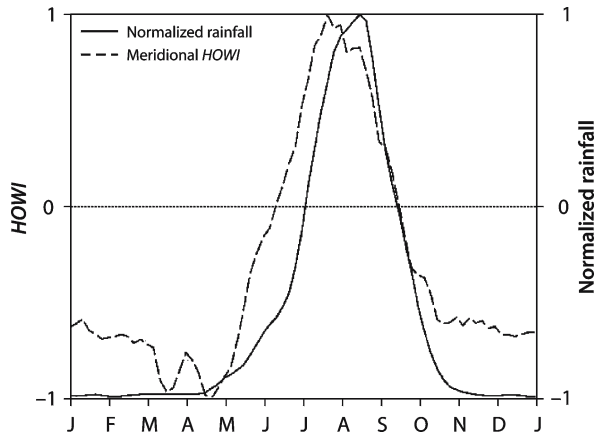


Table 5.1. Summary of the predictive power and use of *HOWI*

	<i>HOWI</i> onset	Rain onset	Rain withdrawal	Time lag onset <i>HOWI</i> – rain	Time lag withdrawal <i>HOWI</i> – rain
WAM Zone	April 1st week	May 2nd week	October 2nd week	7 weeks	0
Sahel	April 4th week	June 2nd week	September 4th week	6 weeks	-0.5
North Sahel	June 2nd week	July 1st week	September 4th week	2 weeks	0.5

atmosphere and ocean. For Africa in particular, more reliable predictions could come with better observational networks both on land and at sea. Dynamical modeling requires a fuller understanding of the relevant oceanic, land-based and atmospheric processes (from local to global scale) which bear on seasonal climate, before models can be constructed to replicate these processes. At the moment these processes are not as well understood as they are for many extratropical regions. For understanding the factors involved in interannual variability, it seems that great efforts should be made towards the following topics:

- Development of methods, both numerical or empirical, for the predictions of local SSTs,
- A better understanding of teleconnection between Indian, Atlantic and Pacific oceans (including ENSO signal) with the beginning and development of West African monsoon,
- A better understanding of influence of synoptic/sub-synoptic factors (like African Easterly Waves and Madden-Julian Oscillation) on the intra-seasonal variability
- An improved understanding of the hydrological cycle with focus on the land/vegetation feedbacks, the relationship with antecedent rainfall and the role of dust and aerosols,
- An improved network of gauges, remote sensing of rainfall estimates and upper air observations in order to better monitor the high frequency signal of West African monsoon that has a relevant impact on seasonal variability.

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Institutionalizing Climate Forecast Applications for Agriculture

A. R. Subbiah · R. Selvaraju

6.1 Introduction

The potential value of seasonal climate forecasts is demonstrated by research studies, which are centered on individual projects (Phillips et al. 2002). Several climate application projects are discontinued by the scientists after signifying the practical value and potential applications. The apparent reasons for discontinuation are financial constraints, changing institutional mandates, personal motivation towards other areas of research and disabling institutional policies. Scientific community is deficient in accessibility to influence the policy to institutionalize the forecasting systems, although policy recognizes the importance of climate forecasts during extreme climate events. In this context, bridging the gap that exists between research, policy and users to facilitate generation and use of climate forecasts was recognized as a challenge (Maria et al. 2002). The sustained operational use or institutionalization of climate forecasts is also constrained by distinct subcultures, institutional attributes of the key players like meteorologists, application scientists and extension personnel. As a result, the key players are very different actors bound by distinct sets of goals and mandates. Differences in disciplinary culture and perspective tend to reinforce the institutional separation (Hansen 2002). Apart from these fundamental ‘cultures’, there are distinct, prominent and motivational factors that influence the sustained generation and use of seasonal climate forecasts. In this chapter, other justifiable factors responsible for institutionalization are discussed with example from Indonesia.

6.2 Institutional Proclivity and Evolution

The institutional proclivity is referred in the context of readiness of the institutions to absorb the new technology available through recent scientific research. The readiness to absorb the forecast technology and further development depends on past experiences of climate related impacts and risk management. Institutions, which pass through a risk management mandate in different context, readily accept and incorporate another emerging risk management strategy. Changes in institutional policies and mandates towards new emerging risks and related motivating factors and needs also influence the proclivity. For example, the Directorate of Crop Protection in Indonesia at the national level was created in 1972 with a mandate to monitor and control pest problems in agriculture. In mid-1980s, there was a considerable shift in mandate; focus on monitoring of flood and drought as a secondary function. In early and mid-1990s, introduction of Integrated Pest Management (IPM) practices and pest resistant

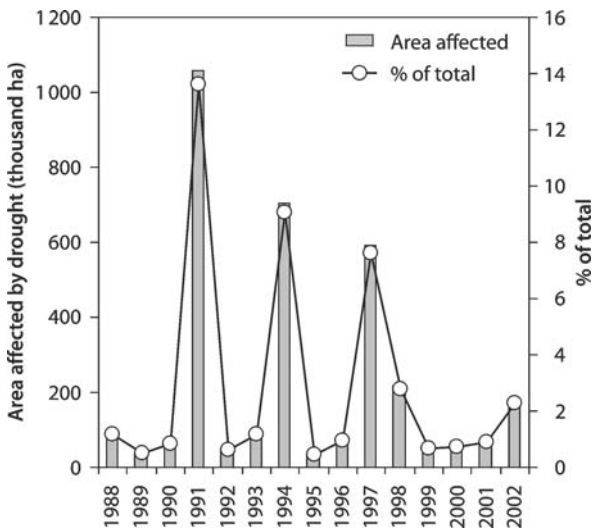
varieties led to significant reduction of pest menace. The IPM schools played a significant role at district level to ensure the lateral seepage of the IPM technology across the villages. After El Niño 1997, the impacts of climate variability on crop production became a major concern.

The institutional set up, which was primarily evolved to monitor pests, provided an opportunity to internalize climate risk management activities within the existing mandate. Though El Niño during 1991 was prominent in terms of rice area affected (Fig. 6.1), institutional transformation had taken place only after 1997 due to availability of El Niño-Southern Oscillation (ENSO) based prediction technology.

Recognizing the importance of pro-active climate risk management the Ministry of Agriculture (MoA) has included climate risk management within Pest Analysis and Disaster Division under Directorate of Food Crops Protection from 2001. Later in 2005, a separate division named the Climate Analysis and Mitigation was formed (ADPC 2006). Initially, the division is entrusted with collection, collation, analysis of long-term climate data and real time drought monitoring. At the district level, the IPM schools were converted into Climate Field Schools (CFS) to match the emerging needs. The farmer field school facilitates practical and field-based learning.

Similarly, Bureau of Meteorology and Geophysics (BMG) of Indonesia was evolved to provide forecast information for transport sector like shipping and civil aviation. In late 1970s, demand for forecast for natural disaster risk management was realized. In 1990s, a series of El Niño impacts diverted attention of climate scientists to generate reliable seasonal forecasts. Availability of usable El Niño forecasts was recognized after 1997 and subsequently there was a growing interest in BMG to address the needs of agriculture and water resource sectors at local level. An inter-agency scientific forum comprising of scientists from BMG, National Agency on Aviation and Space (LAPAN) and Research and Development Department of MoA was initiated. District level science and policy forum was formed to foster development of localized forecasts and to integrate climate risk management in district policy. Recognizing the

Fig. 6.1. Rice area affected by climate risks in Indonesia from 1988 to 2002



institutional changes in agriculture and needs at district level, BMG has readily initiated a replication process in several districts of the country based on the vulnerability and climate predictability.

6.3

Role of Demonstration Studies in Institutionalization

Generally, demonstration studies in climate forecast application are targeting vulnerable areas, which tend to ensure receptivity, participation and commitment of local institutions and community in climate risk management. As beneficial use of climate forecasts depends on high level of human vulnerability, climate predictability and decision capacity (Hansen 2002), demonstration studies automatically target areas satisfying the above criteria. A demonstration study also tries to generate localized climate information, understanding the decision profiles and needs of the farmers. A demonstration study implemented by Asian Disaster Preparedness Centre (ADPC) in collaboration with International Research Institute for Climate and Society (IRI) has followed a well organized sequential process that include: (i) understanding climate variability and impact at local level (ii) farmers need perception, (iii) enabling elements in decision-making environment favoring climate forecast uptake, (iv) assessing institutions generating reliable and usable forecast products, (v) ensuring partnership development, (vi) processing and delivery of localized information, (vii) demonstration of potential value, (viii) policy advocacy and (ix) replication. A demonstration project on climate forecast application in Indramayu district of central Java had motivated the farmers to actively participate in climate field schools and use the climate forecasts to decide about planting method during wet season (Boer 2004).

The lessons learned from the demonstration project have motivated the national partners to expand the project into a national program. In this case, the organized institutional set up is already in place and the demonstration project has just facilitated the institutional linkages at various levels. Institutionalization at national level requires formal arrangement of relevant institutions and their linkages to provide forecast information and a range of other forms of support and policies that foster the provision and use of climate forecasts. It has been recognized that the institutional arrangements play a key role in determining the outcome of climate-related risks (Kirshen and Flitcroft 2000).

6.4

Enabling Local Institutions

Local informal institutions such as agricultural support services (e.g. input supply, agricultural cooperatives, regulated markets, etc.) often take an active role in influencing decisions by promoting new technology. These enabling institutions need to possess important characters like egalitarian, autonomous, self-reliant and democratic to advance sustainable use of climate information. There are many formal institutions at the district levels viz. agriculture, irrigation, public works, planning, budget, trade and commerce, and public health that need to come together and pro-actively decide necessary actions based on climate forecasts. Sustained use of forecasts at local level depends on the coordination of formal, informal organizations and active support from

village development committees, common interest groups and input supply and agricultural cooperatives. The current climate forecast application initiatives in Indramayu, Indonesia hold a promise to bring an institutional set up to strengthen support services to manage climate risks. The lesson learned from the initiative was that the district planning agency had internalized the benefits and is interested to use climate forecasts for district development planning.

6.5 Conclusions

An effective information flow system from forecasters to agricultural organizations and farmers is feasible within the recently evolved institutional system. However, targeted forecast application can be enhanced through developing an end-to-end institutional feedback mechanism (Fig. 6.2). Such applications require significant capacity building efforts at various levels to generate, interpret, translate and communicate usable forecast products.

The effectiveness of institutional features, including organizational structures, policies and supporting instruments like legislation, financial instruments, budget, technology, and partnerships are the attributes that determine the sustained use of forecasts. The demonstration study in Indonesia showed that the bonding of various institutions based on their mandates and norms of solidarity and reciprocity are key elements in strengthening partnerships. As understanding and partnerships grow, these institutions will respond to the emerging challenges and reorient their policies and mandates to accommodate new seasonal climate forecast products. As a result, a growing network with increased capability to manage risk provides a foundation for much greater integration of climate forecasts into decision-making facilitated by enabling institutions.

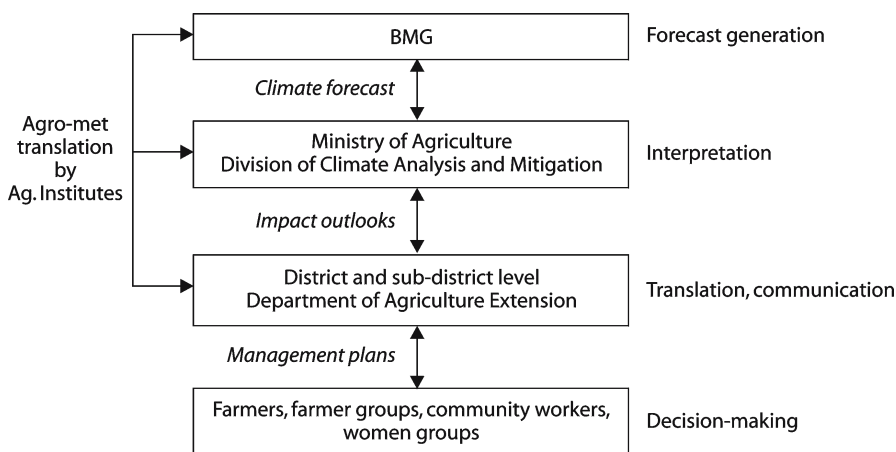


Fig. 6.2. End-to-end institutional system to facilitate the flow of climate information from national to district and local/community levels

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Climate Applications and Agriculture: CGIAR Efforts, Capacities and Partner Opportunities

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7.1 Introduction

Climate variability creates risk in rainfed farming. Risk in turn discourages investment by farmers, governments and development agencies. For instance, in dry regions recurrent droughts debilitate and destabilize poor, agricultural-based societies, and contribute to land degradation by reducing vegetative cover and water supplies. Drought triggers the exploitation of diminishing resources in order to survive (Cooper 2004). Climate change caused by global warming is likely to increase the frequency of climatic extremes in the future and result in changes in cropping practices and patterns over time and space.

If climate variability could be predicted in advance, it would help societies prepare for and cope with the resultant shocks. As well, since drought is a trigger for desertification, better drought prediction and monitoring could help prevent land degradation. This chapter first identifies some key institutional mechanisms of the Consultative Group on International Agricultural Research (CGIAR) for carrying out research to use climatic information in improving agriculture. It then reviews efforts through these CGIAR institutional mechanisms and individual center efforts on climate prediction and adaptation to climate variability, indicating some research highlights and future directions. The CGIAR center's strengths and weaknesses in climate-related work and synergies for potential partnerships are identified, principally with the national agricultural research systems (NARS) and advanced research institutes (ARIs).

7.2 CGIAR Inter-Center Initiatives

The 'Oasis' partnership is the CGIAR's initiative to provide research support to the United Nations Convention to Combat Desertification. Oasis engages seven CGIAR centers, many NARS, UN agencies (UNEP, UNDP, FAO), civil society organizations (IUCN, WWF), NGOs, and ARIs.

Oasis catalyzes innovative research-for-development partnerships among agricultural and meteorological institutions, and with agricultural stakeholders in the public and private sectors. Oasis is currently studying local methods and indicators of drought and desertification, and coping methods, as well as science-generated indicators and new or improved adaptation strategies.

The Desert Margins Program (DMP) is a collaborative effort among nine African countries that include the margins of the deserts that encircle sub-Saharan Africa: Botswana, Burkina Faso, Kenya, Mali, Namibia, Niger, Senegal, South Africa and Zim-

babwe. Rainfall is low and unreliable in these countries. The goal of the DMP is to help these countries arrest land degradation through more sustainable practices and systems that improve livelihoods. The DMP pursues this goal through partnership-based research-for-development activities, demonstration to farmers, and capacity building.

The DMP countries are assisted by five CGIAR centers: ICRAF, ICRISAT, IFDC, ILRI and TSBF-CIAT. In addition, three advanced research institutes from the developed world contribute their expertise in specific areas (CEH, CIRAD and IRD). Regional networks (ASARECA, CORAF, and SADC-FANR) and non-governmental organizations are also core participants.

The DMP is currently executing a major GEF/UNEP project to arrest land degradation, with particular emphasis on indigenous knowledge. This includes local methods and indicators of drought prediction, as well as indicators of drought, and coping methods.

The Virtual Academy for the Semi-Arid Tropics (VASAT) is positioned as a coalition of sources to promote knowledge-sharing in South Asia and sub-Saharan Africa. The coalition membership, which is non-formal, ranges from IARCs and NARS to community-based or rural NGOs. Activities presently take place in both West and Central Africa as well as in South Asia. Lead partners include the Desert Margins Program, along with the ICT/Knowledge Management program of the CGIAR. The Commonwealth of Learning, an inter-governmental organization that promotes non-formal learning, is a key advisor.

VASAT aims to develop climate literacy and drought preparedness among rural communities, development workers, service providers, policy makers, and other strategic sectors through the integrated use of information and communication technology (ICT), open distance learning, and other communication media. It will also communicate information on climatic trends like monsoon behavior and methods of drought management for community mobilization and disaster preparedness.

7.3

Getting a Grip on Variability

Early CGIAR center work by Virmani et al. (1982) documented climatic trends in different regions in India and analyzed their implications for agriculture. This was followed by Sivakumar's seminal work in West Africa (Sivakumar 1988) on predicting variability in the length of the growing season and in soil water content to support crop growth. More recently, this baseline information was used to simulate crop yields in response to different climatic scenarios, e.g. Matthew et al. (1995) and Virmani and Shurpali (1999). In addition, microclimatology work was undertaken to forecast disease and pest incidence such as in Anantapur region, India (Virmani and Shurpali 1999). A third step was to relate these models to economic consequences, and generate policy and technology recommendations (e.g. Harris and Robinson 2001; Shapiro et al. 1993).

7.4

Improving Analytical Tools for Monitoring Drought and Desertification

A dearth of effective, practical tools for assessing and monitoring drought has constrained the fight against desertification. Oasis is fostering the use of quantitative and analytical methods for direct measurements of ecological processes such as evapo-

transpiration from inexpensive, frequently-sampled satellite data (Rosema 1993). These remote sensing analyses are combined with on-the-ground participatory assessments of community perceptions and valuations of drought and degradation. Combined with an understanding of ocean-atmosphere interactions, these tools will significantly strengthen the capacities of communities, nations and regions to develop drought and desertification predicting and coping strategies and tools.

7.5 Predicting Seasonal Rainfall

Historically, there has been a tendency in agricultural research to assume that drought is an unknowable risk. But new understanding of ocean-atmosphere interactions has led to increasingly powerful predictive models for seasonal climatic trends. Columbia University's International Research Institute for Climate Prediction is a leader in this area. They use predicted global sea surface temperatures (SSTs) to drive a suite of atmospheric general circulation models (GCMs). Statistical corrections and optimal combinations of GCMs improve these predictions. By downscaling with dynamic regional climate models (RCMs) and statistical methods, the resolution of these predictions is increased (Hansen and Indeje 2004; Indeje et al. 2000). They have been remarkably accurate, for example in the retrospective prediction of the July-to-September rainfall in the West African Sahel over recent decades, including prediction of the drought years of 1972, 1983, 1987, and 1997. ICRISAT and its partners have also found this method promising in tests in India.

7.6 Predicting Climate Change and Its Consequences

Addressing a much longer time frame, some CGIAR centers are attempting to apply climate modeling to estimate the future impacts of global warming. CIAT and ILRI used a model called MarkSim, which uses data sources from thousands of weather stations worldwide to predict that tropical maize production could decline by 10% by the year 2055 due to global warming (Jones and Thornton 2003). They point out that 10% is merely an average; some areas could suffer much larger losses, with the poorest people being hit the hardest because they are the most dependent on maize as their staple food.

7.7 Effects of Climate Variability on Agriculture

7.7.1 Effects on Crops

CGIAR centers have attempted to adapt crops to variable environments through plant breeding. The largest impacts have been achieved by shortening plant growth duration so that the crop can be harvested before rains cease, i.e. avoiding drought. A more difficult challenge has been to breed traits that enable crops to tolerate drought. Maize in Southern Africa (Bänzinger et al. 2000), pigeonpea in India (Bantilan and Parthasarathy 1998) and barley in the Middle East (Ceccarelli et al. 2004) are just three of many drought-related breeding successes that could be cited.

However, uniformly early-maturing varieties may cause farmers to miss the opportunity posed by the occasional longer, wetter season. Using the mathematical programming method known as 'Discrete Stochastic Sequential Programming' (DSSP), intra-seasonal adaptive decision-making by farmers was modeled at three sites in Niger to understand livelihood strategies that mitigate the impacts of drought and improve incomes (Shapiro et al. 1993). The results lead INRAN, the NARS of Niger, and EARO, the NARS of Ethiopia, to change their breeding strategies to target a range of maturity periods, so that some varieties could always do well despite annual variability in length of the growing season.

7.7.2

Crop-Environment Interactions

The interaction of crop genetics with the environment is also critical in reducing vulnerability to drought. In the Sahel, experts have concluded that nutrient deficiencies are an even greater constraint than low rainfall (Bationo et al. 1998; Breman 1992). Breman (1992) notes that natural vegetation in the 450 mm annual rainfall zone of the Sahel utilizes only 15% of the incident precipitation. The remainder is either lost to evaporation, as runoff or remains in the root zone unutilized. When soil fertility is improved, water use by vegetation can increase to 50% and productivity can increase fivefold, greatly lifting the carrying capacity of the land.

Phosphorus deficiency in the Sahel, for example, renders millet more susceptible to drought; research by ICRISAT and IFDC has found that the application of phosphorus increases plant vigor noticeably, resulting in higher yields and greater drought tolerance, as well as drought avoidance (by causing the plants to mature 1–2 weeks earlier).

7.7.3

Effects on Pests

As crops adapt to climatic change, so will pests. Climate change will favor invasive pests adapted to the new conditions that may devastate the native crops that were never bred to resist them. Periodic episodes of climate change due to the El Niño phenomenon provide a living example of what may happen. In Peru's Cañete Valley, the El Niño episode of 1997–1998 caused temperatures to increase by 3–5 °C and triggered torrential rainfall. This combination coincided with the first discovery of an aggressive new variant of the white fly pest, *Bemisia tabaci* and also the invasion of a species not found there before, *Bemisia afer* (CIP 2001). These species became established and remained even after the El Niño ended, plaguing the important sweet potato and other crops there. This example shows that reinvigorated efforts in integrated pest management and crop resistance breeding will be required to keep up with global climate change.

7.7.4

How Climate Variability Affects People

One particular climate applications gap to which the CGIAR and its partners have tried to respond in recent years has been in helping to find ways to improve sharing of cli-

mate information, technologies, and knowledge with farmers. These efforts have three aspects, first gaining a better understanding of how farmers perceive and respond to climatic risks; second, developing new policy instruments like appropriate drought insurance for poor farmers to help them cope; and third, using new information and communication technologies to share better climate information, recommendations, and policies with farmers.

7.8 Farmer Perceptions of Drought

A recent Oasis study in Burkina Faso (Slegers et al. 2004) found that farmers' perceptions of drought differ significantly from those of research institutions. Farmers are more focused on the agricultural and local-context effects of drought (crop stress, local variations in stress) whereas researchers tend to concentrate on the regional and meteorological aspects (regional rainfall and temperature patterns, soil erosion and impoverishment). To be more relevant, researchers need to translate their macro-level observations into micro-level recommendations that can help farmers reduce their vulnerability under the particular conditions of their own plots.

7.9 Livestock and Drought

ILRI and ASARECA, with USAID support, conducted a survey of 663 households investigating coping mechanisms of pure-pastoralists and agro-pastoralists, during the 1995–1997 drought and 1997–1998 El Niño rains (floods) in Ethiopia, Kenya, Tanzania and Uganda (Ndikumana et al. 2002). The DMP conducted a similar enquiry in Kenya (Anonymous 2004). The majority of respondents among four tribes in dry areas of Kenya were aware of traditional signs that they felt had predictive power for weather, vegetation and soil conditions. Systems analysis revealed a number of opportunities to help herders improve their preparation and coping strategies.

If droughts could be foreseen longer in advance, herdsmen could reduce herd size in an orderly way, avoiding panic sales. Cooperative action among herders could avoid them being exploited by middlemen e.g. in panic sales of livestock that depress markets and strip the herders of their capital assets. Coordinated downsizing and rebuilding of herds could reduce market squeezes and gluts. Better health care for animals during droughts could increase survival rates. Better range management and the creation of fodder banks could ease the dry-season feed constraint.

7.10 Drought Insurance to Help Land Users Manage Climatic Variability

Climatic variation is an age-old risk of farming. Its consequences are severe and can wipe out livelihoods. This risk may increase as global warming increases the frequency and intensity of climatic extremes.

A conventional way of mitigating risk is the use of insurance. However, conventional approaches to insurance bear high costs and may even create perverse incentives. For example, government relief aid tends to favor wealthier individuals who took greater

risks (and therefore suffered greater losses) by cropping or grazing livestock herds in drought-prone areas, for example. This form of insurance is high-cost and encourages even riskier behavior in the future.

An alternative being developed at IFPRI is private-sector insurance tied to objective, easily-monitored weather indicators such as rainfall levels (Skees et al. 1999). Farmers buy policies based on the size of their farm operation (or their judgment), so that larger risk-takers pay appropriately more to insure larger operations. If rainfall, for example falls below the pre-set minimum for a season, the insurance claim becomes valid. Insurance companies are able to accurately predict the risk and therefore calculate an appropriate premium, since there is a wealth of historical rainfall data available for most areas of the world. This approach would shift the insurance burden from the public to the private sector, and make it more efficient and equitable.

7.11

Information Technology for Knowledge-Sharing

VASAT uses the Internet, radio and other electronic means to prepare dryland farmers for drought and to help cope with it when it occurs. A hub-and-spokes model is followed (PANTLEG 1999). A central village with road access and electricity serves as an Internet or radio transmission point to reach surrounding hamlets. Receiving systems in the hamlets may be solar or battery-powered, or simply use personal radios. Village moderators in each hamlet consult with residents to gather their information needs and relay them to the hub, which collects the needed information and transmits it back to the hamlets, expressing it in the local language and displaying it through simple media such as bullhorns and chalkboards (and over the radio).

This telecenter/radio platform can also be used for conveying learning modules, gathering and relaying drought warning information, government assistance programs, market prices, and many other valuable types of information.

7.12

Conclusions: Future Climate Applications in CGIAR Centers and Partnership Opportunities

Since early efforts, little further work has been done by the CGIAR in modeling for climate prediction. The CGIAR has judged it does not have comparative advantage to pursue this type of work that is being done by ARIs like IRI. However, because of its location in developing countries, the CGIAR has a comparative advantage to continue to help partners in developing crop yield simulation models with ARI partners, making use of available weather and climate predictions. There are also continuing opportunities for the CGIAR to play a leading role in using these weather driven models to develop adaptive agronomic recommendations and do ground-truthing of these recommendations through field trials, both scientist and farmer managed, with NARS partners. CGIAR centers can also continue to make strong efforts in combining geographical information systems and climate simulation modeling with particular emphasis on the agricultural consequences of climatic variability, especially global warming.

The CGIAR, meanwhile, has made little progress in combining crop simulation and bio-economic optimization modeling to develop adaptive technology recommendations. Opportunities for partnerships in this area exist with North American and European universities such as Purdue University and Wageningen University, and with ARIs such as IRI.

The local consequences of global warming are difficult to predict; some areas may get drier and hotter, others wetter and cooler (Parry 2002). Therefore the centers are developing a range of scenarios so that countries can prepare for whatever they may encounter. As time goes on, these scenarios can be refined to match observed trends and narrow the response options to fewer, more likely alternatives. Partnership opportunities will exist in the linking of biological to economic criteria in these models, a major current challenge already starting to be tackled by some centers. Such bio-economic modeling is essential because decision-makers tend to rely most heavily on economic valuations. The agro-biodiversity costs of climate change, for example, could include higher food prices and less reliable food supplies (e.g. if major food-producing regions decline) (Rosegrant et al. 2002). Decreasing water supplies in some areas could raise the costs of irrigation (or make it unfeasible) while floods and droughts could create major costs in different sectors of the economy.

Since global warming appears inevitable, much CGIAR research will continue to be geared towards reducing vulnerability by adapting crops, land use systems and policies to likely scenarios. This involves work in plant breeding, integrated pest management, natural resource management, socio-economics and policy, and related topics that can be done with both NARS and ARIs.

The CGIAR can also lead (as currently exemplified by CIAT and ILRI) in the use of long-term climate prediction to analyze expected changes in cropping patterns over time, those due not only to climatic factors but also those due to changes in biotic stresses such as pests and disease.

Lastly, the CGIAR is looking for partners in its efforts to find ways to improve the sharing of climate information, technologies, and knowledge with farmers.

There is thus ample opportunity for the CGIAR to work with those who are developing better climate applications to improve agricultural productivity and reduce climatic risk.

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Institutional Capacity Building in Developing Countries through Regional Climate Outlook Forums (RCOFs) Process

K. A. Konneh

8.1 Introduction

Climate affects the lives of all living beings on earth. Every system is vulnerable to climate, and the impact of climate extremes can cause devastating damage to people and their economies and environment. This vulnerability, however, varies from region to region, and is a function of many factors, such as the geographic location, resiliency, capacities (economic, technical and financial), social capital, political environment, and livelihood security.

Developing countries have the least technical and financial capacities to cope with the impacts of climate variability. This situation predisposes them to greater vulnerability to climate risks than the industrialized and developed countries, which possess adequate capabilities and resilience to cope with climate variability. Most countries in Africa, especially those in the sub-Saharan Africa (SSA), are characterized by diverse livelihood security systems such as pastoral, rainfed agriculture, and cash crops. Developing countries largely depend on precipitation for the productivity of these systems. The developing countries' reliance on natural resources such as precipitation for economic development and livelihood security makes these countries extremely susceptible to seasonal to interannual climate variability. The relatively poor economies and weak institutional infrastructures of these regions further compound the problem. According to the IPCC Third Assessment Report (McCarthy et al. 2001), the global average surface temperature increased in the last century, and it will continue to rise in the current and future centuries. This environmental dynamic will, however, vary by region, and will be accompanied by significant changes in precipitation, sea level rise and frequency and intensity of extreme events such as droughts, hurricanes and floods. These changes will affect all regions, but the developing regions such as Africa, Latin America and the Caribbean, Southeast Asia and the South Pacific with the least technical and economic capabilities to plan, respond and adapt, will be the hardest hit by the impacts of climate variability and change.

Developing countries, therefore, need to be given the opportunity to take advantage of the recent advances in climate science and technology, which would assist them in reducing their vulnerability to climate variability and change. Such technology can also increase their resilience and develop sustainable strategies to effectively adapt and cope with climate variability and change. The vulnerability of developing countries is further compounded by their predominant dependence on agriculture, a system whose fate is intricately tied with availability of sufficient soil moisture during the production season. Knowledge of the coming rainfall seasons is, therefore, critical for farmers. This information would help farmers to modify farm management decisions that

would help reduce their ex-post production losses, such as crop yields. In the developing countries, agriculture is the main driver of their economies and can contribute an estimated 75–80% to the gross domestic products (GDPs) of these countries. Unfortunately, this sector is notoriously vulnerable to climate variability due to its dependence on precipitation, a variable that is likely to influence crop or livestock products.

Understanding the dynamics of climate variability and the role of climate variability in human affairs, and using the understanding as a basis for highly interdisciplinary, problem focused research that results in new information and options for decision-makers struggling to manage climate risks, such as droughts and floods, should be a priority. This is especially true for those developing countries that are disproportionately more vulnerable, and have the least capacity to respond to climate risks. The research efforts would, therefore, require involvement of many players, especially from the developed nations of the U.S. and Europe. The developed countries have cutting edge technologies such as seasonal climate forecasting that the developing countries can access through international research collaboration. This chapter highlights institutional and scientific advances and challenges of capacity building that have emerged out of the COF process. The chapter also identifies the main regional and international partners and collaborators, including their roles in the regional and national institutional capacity building, that has emanated from the Climate Outlook Forums (COF) process.

8.2 Origin of the COFs

In 1995, a select group of scientists from the U.S. and elsewhere, including countries of Africa, convened a small meeting in Washington D.C. to explore the possibility of providing the developing countries the opportunity to benefit from advances/research in climate science (seasonal forecasting) to reduce their vulnerability to climate risks such as droughts, floods, tropical cyclones, forest fires, etc. This meeting was followed by a workshop: “*Reducing Climate Related Vulnerability in the Southern African Region*” (NOAA-OGP Report, 1996). One of the recommendations of this workshop was to find a way to help developing countries understand the role of climate variability, and to use this knowledge to help reduce their vulnerability to climate risks through the use of seasonal climate forecast information. Climate experts and policy makers who participated in the workshop recommended the COF process as an appropriate vehicle to provide not only climate information, but also capacity building to apply and utilize the information.

8.3 COF and Associated Institutional Synergies

COF is a coordinated and collaborative effort of NOAA and a range of partners, such as the USAID-OFDA, the World Bank, the World Meteorological Organization (WMO), etc., designed to give decision-makers in climate sensitive sectors such as agriculture, water resources, guidance on the status of the approaching rainfall season. The use of this guidance would help to reduce the impacts of climate risks.

The COF processes have now evolved into a well-defined international procedure for the annual preparation, dissemination, and verification of research based seasonal rainfall forecasts for developing regions such as Africa. Decision-makers in these regions have used the forecasts in the various climate sensitive sectors for strategic management decision, such as decisions on type of farm management practices based on a given seasonal forecast. The COFs have improved institutional capacities, promoted regional cooperation and integration, especially among the National Meteorological and Hydrological services (NMHSs), policy makers and the user communities in the developing regions. This cooperation has contributed to creating institutional building blocks, both at regional and community levels, for effective response and planning to reduce the impacts of hydro-meteorological disasters such as droughts and floods.

The COF process brings together many regional and international scientists, policy and decision-makers, non-governmental organizations (NGOs), public sector institutions and intermediaries of information communication, such as the media and extension. Participating institutions in the process are: WMO, IRI, NGOs, NMH, donors (NOAA, USAID-OFDA, World Bank), universities, research institutions, UK Meteorological Office, the U.S. National Center for Environmental Prediction-Center for Climate Prediction (NCEP-CPC), Inter-American Institutions for Global Change Research (IAI) in Latin America and the Caribbean, the Asian Disaster Preparedness Center (ADPC) and the Famine Early Warning System Network (FEWS NET). The bringing together of multidisciplinary groups such as policy makers and scientists in a forum process has contributed to useful dialogues, discussion of the forecast information, and creation of an effective feedback loop between the information producers and users. From the inception of the COF process its products have, therefore, been the most credible and legitimate source of climate information to decision-makers for climate-related decision-making.

8.4

Capacity Building of the National Meteorological and Hydrological Services (NMHSs)

The COF process involves training of the NMHS staff in the different regions of Africa, Latin America and the Caribbean, Southeast Asia and the South Pacific. The training focuses on the understanding of the dynamics of climate variability as influenced by major climate forcing such as El Niño-Southern Oscillation, the Pacific Decadal Oscillation, and the Indian and Atlantic Oceans. In the pre-COF era, the NMHS had very little or no knowledge of using the ocean-atmosphere dynamics to forecast climate three months in advance. In other words, these institutions in developing regions did not have knowledge of seasonal to internal climate forecasting. Instead, they typically limited their forecasting efforts to predicting three to five day weather reports. A pre-forum capacity building component of NMHS staff is an integral part of the COF process. This component has improved the institutional capacity of the NMHS staff from doing simple statistical modeling to dynamical modeling, a more sophisticated scientific method that better captures the chaotic nature of the climate system. The collaboration and partnership between the regional and international institutions such as the IRI, the regional WMO specialized centers, the U.S. NCEP/CPC-African Desk,

have contributed to the advanced institutional capacity of the NMHSs in developing countries. From the recommendations of the COF process, the USAID-OFDA and WMO provided support for a dynamical modeling laboratory at the Inter-Governmental Authority on Development's (IGAD) Center for Climate Predictions and Application Center (ICPAC), formally known as the Drought Monitoring Center (DMC) Nairobi. This positive synergy has contributed to dynamical modeling capability of the regional NMHSs staff in the Greater Horn of Africa (GHA) commonly known as Eastern Africa.

8.5

Capacity Building of Users of Climate Information

Providing skilled climate information does not guarantee the use and application of information by the users (Jones et al. 2000; Walker et al. 2001; Philips and Orlove 2003; Patt et al. 2005; Emmer et al. 2003). There are numerous barriers to the use of the information. Some of these are communicating the information, and providing the right type of information for the user. These important gaps between the information providers and users will be filled through appropriate training of the users to understand the language of the information and further research by the providers of the information to perceive a holistic decision context of the users (Hansen et al. 2004).

In addition to providing seasonal climate outlooks, users' capacity building has been an integral part of the COF process. Water resources managers have received training in factoring climate information into water resources management (GHA Workshop, 2002).

Food security and agriculture sector managers received training in downloading probability forecast for agricultural applications (GHACOF 2003).

In the Southern African Development Community (SADC) region, the livestock industry is a major livelihood system and a major contributor to the economies of the region. In 2004, part of the COF process for the region was an institutional capacity training of livestock managers to factor climate information in the management of the livestock industry (SADC Livestock Workshop, 2004).

8.6

Capacity Building of Journalist Institutions

The 2000 Global Review of Regional Climate Outlook Forums identified an inadequate participation of the media in developing countries to communicate climate information. This may be a major impediment to effective use and application of climate information in these countries (Basher et al. 2000). Reacting to this recommendation from 2001 to date, NOAA and partners have supported a number of climate and media training workshops as part of the COF process, especially in the African region. The first regional media-climate training was held in Dar Es Salaam, Tanzania in 2001. This training brought together 30 journalists and 20 operational forecasters in an interactive forum in which forecasters trained journalists in the fundamentals of seasonal forecasting, interpreting the language of forecasting, and the role of media institutions in communicating climate information (Media workshop, Tanzania 2001).

Similar institutional capacity building activities have been implemented in the African region for journalists and editors (Luganda 2003; Dlamini 2002; Ogallo 2004;

Islam 2003). The institutional capacity building of the media experts has resulted in a greater collaboration between the media and the operational forecasters and has led to enhanced communication and interpretation of the technical language of the probability forecast. Additionally, the training and collaboration between operational forecasters and the media has resulted in establishing media networks of climate journalists in both the GHA and the SADC sub-regions. These networks are now engaged in specialized reporting on hydro-meteorological disasters such as droughts and floods (SARCOF8 2004; GHACOF 2003).

8.7

Improving Regional and National Scientific and Climate Research Capability

Pilot application projects are outgrowths of the COF process. These projects are designed to develop new methodologies or enhance existing ones to apply climate information, assess the communication of climate information and identify impediments to effective utilization of climate information. NOAA and partners have supported regional and national institutional and individual scientists from operational forecasting institutions (NMHSs), the agriculture and food security sector, research institutions and universities. These scientists have conducted exploratory and pilot research to address critical climate related issues such as disaster management, drought and food security and hydropower resource management. Some of the regional scientists are now working with international institutions such as the IRI to upgrade some of the pilot projects into operational mode (Oludhe 2001; Mhita et al. 2003; Githeko and Ndegwa 2001; Walker et al. 2001). The institutional capacity building activities, however, face critical technical and institutional challenges, which interested partners need to address to enhance and sustain existing trade-offs, and create new ones.

8.8

Institutional Challenges

Most important of the challenges is the sustainability of the process in the long run. From the inception of the capacity building activities, international donor organizations such as NOAA, USAID-OFDA, the World Bank and WMO, have provided the funding. Up to now, there is no concrete strategy for other options at local or regional level to take full responsibility of the process, especially the COF process. This challenge threatens the future continuity of the COF process and its associated capacity building activities. The future fate of the capacity building activities is not clear, especially if the current donors cease funding, and there are no alternative options to take up the funding responsibility. COF is an endangered species under the current circumstances and it needs help to save and sustain its life. Another institutional challenge is mainstreaming of the COF products into routine regional and national development planning activities. This can influence users' perception, trust and confidence in the information, which, in turn, are linked to the quality and skill of the product. This is a technical issue, which would be resolved by addressing critical technical challenges.

8.9 Technical Challenges

COF products are still general. Some questions are still unanswered:

- Is it appropriate to plant at all, based on the given seasonal forecast scenario?
- Which kinds of crops and varieties will be suited for a specific season and for a specific location?
- When should farmers plant? and what is the optimum planting density based on the nature of the upcoming season?

The users' knowledge of the uncertainties of the probability forecast is still low. The providers of the information need to make further efforts to help decision-makers better understand the uncertainty of the information. The language of the current forecast is too technical and not user friendly. These factors impede the mainstreaming of the information into decision-making and routine regional and national development planning activities.

8.10 Conclusions and Recommendations

In conclusion, the associated COF processes (capacity building activities) have established a regional mechanism through pilot projects to demonstrate place-based opportunities and challenges of applying seasonal forecast for disaster reduction in the region. Additionally, the capacity building effort has resulted in a well-recognized international framework, the Climate Outlook Forums, which generate and disseminate experimental forecasts for disaster reduction in the region. This framework is now the most credible and legitimate source of climate information decision-makers utilize to plan and respond to hydro-meteorological disasters in the region. Some of the emerging institutions such as the networks of climate journalists (Network of GHA Climate Journalists and the Southern African Development Community (SADC) Climate Journalists) have resulted in improved reporting of climate information, improved collaboration and understanding between the media institutions and the operational forecasters in the GHA and SADC sub-regions. Some journalists in these sub-regions now engage in specialized reporting and work with operational forecasters on a continuous basis to monitor and report on indicators of any emerging climate related extremes instead of waiting to report disasters.

In spite of the positive spin-offs of the COF process as outlined in the previous sections, the future of the process and its institutional capacity building activities is not bright, if all players, such as the policy makers and scientists, do not resolve the existing institutional and technical challenges facing the process. The responsibility squarely lies on regional governments and interstate institutions in developing regions that benefit from the COF process. Non-governmental organizations (NGOs), the World Food Program (WFP) and humanitarian institutions that benefit from seasonal forecasts should integrate the cost of capacity building activities into their regular development program as a requirement driver in order to justify budgeting for COFs and related activities.

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Use of ENSO-Driven Climatic Information for Optimum Irrigation under Drought Conditions: Preliminary Assessment Based on Model Results for the Maipo River Basin, Chile

F. J. Meza

9.1 Introduction

Water is a fundamental resource to ensure agricultural productivity. Access to hydrological resources to supplement rainfall during the growing season is seen as one of the key issues for food security. For this reason, the development of agricultural systems in arid and semi-arid regions has been closely linked to the scientific and technological advances in irrigation engineering.

When water is not a limiting resource, crops can achieve high levels of productivity because the absorption of nutrients is carried out normally and the stomata are fully open, allowing gas exchange (i.e. water vapor and carbon dioxide) in an adequate manner. However, when crops are experiencing water deficits, several regulatory mechanisms take place resulting in a reduction of dry matter assimilation, mainly because the resistance to gas exchange is increased due to stomata closure, and the absorption of mineral nutrients is affected. Given the strong relationship between water transpired and dry matter accumulation, irrigation seeks to provide crops with timely water supply and in the quantities needed so that physiological stress is minimized and crops can express their yield potential (Chang 1968; Norero 1999). Two important conditions support the operation of irrigation systems in such conditions: (1) the correct estimation of crop evapotranspiration and (2) access to sufficient water resources so that the agricultural water demand can be effectively met.

The problem of irrigation management is far more complex in situations where there is a deficit in water supply. In this case, resource constraints redefine the situation, and the decision-maker seeks to reach the maximum feasible productivity of the agricultural system, particularly when several crops are competing for the limited resource, which is a traditional resource allocation problem. Decision theory states that an optimum allocation of resources is achieved when the decision-maker knows the consequences associated with all possible combinations of alternatives and states of the variable. Because climate is one of the main factors that generates uncertainty regarding final yields and given the interdependence of irrigation allocation decisions throughout the growing season, access to reliable information (i.e. climate forecasts) can generate additional economic benefits, being a tool for irrigation management.

This work illustrates the potential use of climate forecasts based on El Niño phenomenon for irrigation operation under limiting water supply conditions in central Chile, a region that has shown a significant ENSO footprint in its climatic regime. Using a methodological framework that combines stochastic modeling of meteorological variables conditioned on El Niño phases, a simple soil-crop algorithm, and a mathematical programming model, the value of climatic information is assessed. Section 9.2

summarizes the impacts of El Niño phenomenon on the climate of central Chile and the effects of climate variability on agricultural systems. Section 9.3 describes the methodological framework used to evaluate the potential additional economic benefits associated with ENSO forecasts for a case study in central Chile. Finally, Sect. 9.4 presents the results of the case study and the main conclusions of the work.

9.2 Climate Variability and Agricultural Systems

According to Oram (1989), agriculture represents one of the most weather dependent productive sectors. In addition to that, it is also the largest consumer of water resources due to the extensive surface that crops utilize during their development. Rosegrant et al. (2000) identify climate variability and the growing competition for water among economic sectors as two key issues that a modern society has to face when designing efficient water allocation policies.

Given the sensitivity of agricultural systems, in situations where timely and skillful climate forecasts are available, such information could be of great value as long as the system shows a response to the climatic signal and there are alternatives that can be targeted to the forecast resulting in different optimal strategies of water resources management.

One of the most simple but useful forecast system corresponds to the use of climatic signals. These can be identified, monitored, and used as a forecasting tool in order to estimate possible scenarios of weather sensitive systems. This is the case of El Niño-Southern Oscillation phenomenon which has been described as a factor that can explain an important fraction of climate variability in several parts of the world (Walker 1923; Ropelewski and Halper 1996). As other parts of the world, the climatic regime of central Chile is exposed to important fluctuations that, up to some extent, can be associated with El Niño phenomenon. In central Chile, changes in the precipitation regime have been studied and associated with the Southern Oscillation Index (*SOI*), which points to a tendency to observe anomalously dry conditions during the positive phase of the Southern Oscillation (La Niña phase) (Rubin 1955; Pittock 1980a). In addition to that, precipitation is likely to be abundant during the Niño years, corresponding to the negative phase of the *SOI* (Quinn and Neal 1982).

Temperature changes have also been studied by Pittock (1980b) stating that there are warm temperature anomalies in conditions where sea surface temperatures are above the mean (El Niño years). Rosenblüth et al. (1997) showed that there is a negative correlation between mean temperatures and the Southern Oscillation Index with a tendency to be warmer during the negative phase of *SOI* (corresponding to El Niño years) and colder when La Niña is present (positive phase of *SOI*).

Daily meteorological variables have also been studied conditioned on El Niño phases. Maximum, minimum and dew point temperatures as well as wind speed were analyzed by Meza et al. (2003). They concluded that the influence of El Niño phenomenon is not as marked as in the case of precipitation. However, the precipitation regime does affect other meteorological variables because there are differences between days with and without precipitation. It was later demonstrated by Meza (2005) that El Niño does have an influence on reference evapotranspiration in central Chile becoming a phenomenon that would represent an important tool for water resources

management. It was found that agricultural water demands can be up to 20% higher during La Niña years.

Several studies show how climatic information derived from ENSO forecasts can be used to accurately estimate yield outcomes and crop water demands. Yield responses as a function of ENSO phases are illustrated for several crops and agricultural systems (Phillips et al. 1998; Podestá et al. 1999). It has been also shown that the use of climate forecasts can bring additional economic benefits because the decision-maker can target specific management strategies to the future forecasted events (i.e. there is an economic value in climate forecasts). Examples of such work are found in Adams et al. (1995), Messina et al. (1999), and Hammer et al. (2001). For central Chile the value of ENSO-driven climate forecast has been estimated for perfect and imperfect knowledge of future El Niño phases for different crops and agricultural systems (Meza et al. 2003).

A straight forward way to analyze the response of crops to climatic variability throughout water use (and therefore irrigation) can be done by looking at the water use efficiency factor, defined as biomass generated per unit of water transpired. To represent this situation, Doorenbos and Kassam (1979) define a K_y coefficient, which is known as yield response to water factor. The general equation proposed is:

$$\left(1 - \frac{Y_a}{Y_m}\right) = K_y \left(1 - \frac{ET_a}{ET_c}\right) \quad (9.1)$$

Here, Y_a is the actual yield of the crop (kg ha^{-1}), Y_m corresponds to the maximum yield (kg ha^{-1}), ET_a is the actual crop evapotranspiration (mm), and ET_c the potential crop evapotranspiration (mm). A K_y value less than one means that the crop shows less sensitivity to water restrictions, whereas a K_y value higher than one implies that the crop is highly susceptible to water stress. Even though it is a useful relationship for irrigation planning, there are some ambiguities in applying this method for optimum water allocation. The authors do not consider successive and different levels of water stress which may occur in reality. It is not clear whether the method has to be applied in multiplicative form (i.e. the effect of the stress in one stage is carried to the following stage) or taking the minimum value of all stress stages.

Jensen (1968) proposed a mathematical relationship that is easier to apply and considers the effects of individual non equal levels of water stress over crop yield. The Jensen model is:

$$\frac{Y_a}{Y_m} = \prod_{i=1}^4 \left(\frac{\sum_j ET_a}{\sum_j ET_c} \right)^{\lambda_i} \quad (9.2)$$

where λ_i is the stress sensitivity index for each developmental stage i ($i = 1, \dots, N$). For each crop $i = 1$ corresponds to the vegetative phase, $i = 2$ is the flowering phase, $i = 3$ is

the fruit development phase, and $i = 4$ represents the harvest phase. The variable j represents the number of days in each phase i .

Note that, under drought conditions, decisions made on early stages regarding to the amount of water allocated may affect final yield, either by restricting the rate of actual evapotranspiration in the current period and/or affecting the future ones because they determine the soil water content that will be available in subsequent periods. For this reason information regarding future water demands (ET_c) may be useful to define an optimum irrigation management.

9.3 Methodological Framework

Although, El Niño phenomenon mainly affects the precipitation regime of central Chile, the study is carried out considering crops that are grown during the austral spring and summer (October to March). Being a Mediterranean climate, only the effects of ENSO on atmospheric water demands are considered. Following the definition of El Niño given by Trenberth (1997), daily meteorological records for the period 1976 to 2003 at the location of Pudahuel (33.27° S) were classified in the different phases of El Niño. A “weather generator” conditioned on El Niño phases (Wilks and Wilby 1999) was fitted and used to generate synthetic series of daily meteorological variables that were combined to generate estimates of reference evapotranspiration using Penman-Monteith formula (Monteith and Unsworth 1990), more details of the weather generator algorithm can be found in Meza (2005).

The soil unit selected corresponds to the Maipo soil with the following characteristics: 1.2 m depth, 34.8% sand, 21.2% clay, bulk density equal to 1.3 g cm^{-3} , and a water holding capacity of 80 mm. Due to the lack of information about saturated hydraulic conductivity, water flow in the soil was simulated at a daily time step using a tipping bucket approach.

A farming system composed by 1 ha of tomato, 1 ha of watermelon, and 1 ha of potato is used in this example. The problem corresponds to an optimal allocation of limited water resources among the different crops with the general objective of maximizing the net benefits of the farm.

It is assumed here that all crops have the same growing period with sowing date set to 1 October, and with an extension of 182 days (exactly six months). The yield at the end of the growing season is simulated by the Jensen’s model (Eq. 9.2). Each crop is grown in the same type of soil with maximum water holding capacity of 80 mm and initial water content of 50 mm.

For simplification it is assumed that water for irrigation (Q_l in mm) is available in fixed and known amounts and can be applied as a discrete variable to each crop irrigated (0, 5, 10, ..., X). The irrigation is made on fixed dates with a frequency of 10 days and without the possibility to store it for subsequent periods. In this way there are 18 times 3 possible irrigation amounts represented by $X_{l,k}$ (l dates and k crops). Since the Doorenbos and Kassam work contains information about the K_y factor for several crops that are relevant to this study, it is necessary to adapt their method into a simpler one like the Jensen’s model. The solution to this problem is presented by Kipkorir and Raes (2002) transforming the K_y factor into the Jensen’s sensitivity index (λ) as:

$$\lambda = 0.2757K_y^3 - 0.1351K_y^2 + 0.8761K_y - 0.0187 \quad (9.3)$$

The nonlinear mathematical model is represented as:

$$\max_{X_{1,1}; X_{1,2}; \dots; X_{l,m}} (\Omega) = \sum_{k=1}^3 P_k Y_k \tag{9.4}$$

For each irrigation moment, the constraints of the system are represented by the following equation:

$$\sum_k X_{l,k} \leq Q_l \tag{9.5}$$

The parameters used in this example are presented in Table 9.1 and the mean values of reference evapotranspiration are presented in Table 9.2. Note the differences between the sensitivity of different crops to water stress and the mean values of crop potential evapotranspiration between El Niño phases.

In the absence of information a farmer will select an irrigation strategy based on the expected value of crop evapotranspiration (i.e. the weighted average of ET_c across all El Niño phases) and water availability, creating a Ω_c function as:

$$\Omega_c = \max_{X_{l,k}} \left(\Omega \left(X_{l,k}; E \left(ET_{c,l,k} \right), Q_l \right) \right) \tag{9.6}$$

To estimate the potential use of El Niño-driven climate forecasts, it is necessary to compare the performance of the farmer described above with one that has some information about the future possible states of ET_c . This farmer will choose an irrigation strategy conditioned on the expected value of crop potential evapotranspiration under the correspondent El Niño scenario and water availability (Ω_e under El Niño events, Ω_n under normal events, and Ω_a under La Niña events). These functions are represented by:

$$\Omega_o = \max_{X_{l,k}} \left(\Omega \left(X_{l,k}; E \left(ET_{c,l,k} | o \right), Q_l \right) \right) \tag{9.7}$$

with $o = e, n, a$ following the notation described above.

It is assumed here that El Niño conditions for the whole growing season are known at the beginning, in that sense it represents a case of perfect information about El Niño phases, although there is uncertainty about crop evapotranspiration within each phase. Under maximization criteria if the irrigation strategies selected in Eqs. 9.6 and 9.7 do differ, the information about future El Niño conditions has a potential economic value (i.e. there is an economic incentive for the farmer to use climate forecasts based on El Niño events). The relative frequencies of the phases of El Niño for the growing season considered here are: $P(e) = 0.33$; $P(n) = 0.41$; $P(a) = 0.26$.

Using approximate moments analysis, the expected value of the use of ENSO information (*EVI*) in this optimum irrigation problem is calculated as:

$$EVI = \sum_o \Omega_o P(o) - \Omega_c \tag{9.8}$$

Table 9.1. Parameters used in the mathematical programming model for each crop

	Tomato	Potato	Watermelon
Price (U.S.\$ t ⁻¹)	250	220	320
Y _m (t ha ⁻¹)	65	50	40
λ ₁	0.33	0.37	0.62
λ ₂	1.15	0.74	0.74
λ ₃	0.74	0.62	0.74
λ ₄	0.33	0.15	0.24

Table 9.2. Mean values of crop potential evapotranspiration (*ET_c* in mm.) for the different phases of El Niño. T = Tomato, P = Potato, W = Watermelon

Period	La Niña			Normal			El Niño		
	T	P	W	T	P	W	T	P	W
1	13.4	13.5	13.3	14.0	14.1	13.9	12.2	12.3	12.1
2	15.8	16.2	15.4	16.9	17.4	16.5	14.9	15.3	14.6
3	17.5	18.3	16.9	19.2	20.0	18.6	17.2	17.9	16.6
4	25.5	26.9	24.5	26.8	28.3	25.7	23.0	24.3	22.0
5	28.1	30.0	26.8	29.7	31.7	28.3	26.9	28.7	25.6
6	31.1	33.7	29.4	33.3	36.1	31.5	30.8	33.4	29.1
7	36.9	40.2	34.2	39.0	42.5	36.1	36.7	40.0	34.0
8	42.1	45.5	38.4	44.0	47.6	40.2	40.8	44.2	37.3
9	44.4	47.7	40.5	47.7	51.3	43.5	45.0	48.4	41.0
10	50.6	54.1	46.0	51.7	55.4	47.1	50.5	54.0	46.0
11	51.4	51.9	46.8	55.3	55.8	50.3	54.9	55.4	50.0
12	50.8	48.9	46.1	54.0	52.0	49.1	53.0	51.0	48.1
13	49.0	47.1	44.5	51.7	49.7	46.9	50.4	48.5	45.8
14	46.3	44.5	42.0	48.0	46.1	43.5	43.9	42.2	39.8
15	41.9	40.2	37.9	43.3	41.5	39.2	41.2	39.5	37.3
16	34.6	32.9	31.0	35.4	33.6	31.7	34.7	33.0	31.1
17	28.4	28.1	26.4	29.2	28.9	27.1	29.8	29.5	27.7
18	21.6	23.6	22.1	22.3	24.3	22.7	21.6	23.6	22.1

9.4 Results and Discussion

Different levels of water availability, expressed as equivalent millimeters of water, were included in this study to represent a wide variety of situations, ranging from no deficit ($Q = 175$ mm) to severe water scarcity ($Q = 25$ mm). As a first approximation *EVI* was assessed considering a farmer that bases his allocation only on expected mean values of crop potential evapotranspiration and does not measure the real values of the variable in the current and previous periods. In that case no further revision of the allocation strategy is possible. Clearly, the value of information received at the beginning of the growing season has more value for this farmer than for a decision-maker that updates the knowledge of the system with actual measurements. Figure 9.1 presents the results of *EVI* disaggregated for each phase of El Niño. *EVI* is present in all phases of El Niño when available water for irrigation has a value between 25 and 175 mm, reflecting that an allocation using ENSO-driven climate forecasts has a potential use. The weighted average of *EVI* values ranges from 35 to 200 U.S. dollars depending on the magnitude of the constraint. When available water is higher than 175 mm, the total satisfaction of crop requirements is achieved (i.e. an unconstrained maximization is observed) and, irrigation is therefore the simple management of the soil water budget. On the other hand, when available water is below 25 mm, no differences in water allocation strategies are found because the decision-maker is forced to irrigate the crop with maximum marginal productivity.

It is also possible to estimate the *EVI* for a decision-maker that revises his allocation strategy incorporating the realization of previous and observed values of crop evapotranspiration. For this farmer it is possible to correct the wrong estimates of ET_c with real values. In this case the value of information derived from future conditions of El Niño is reduced. However due to the time dependence of previous decisions and their effect on final yield, *EVI* is never equal to zero. This feature can be observed looking at the evolution of the objective function of the decision-maker that allocates wa-

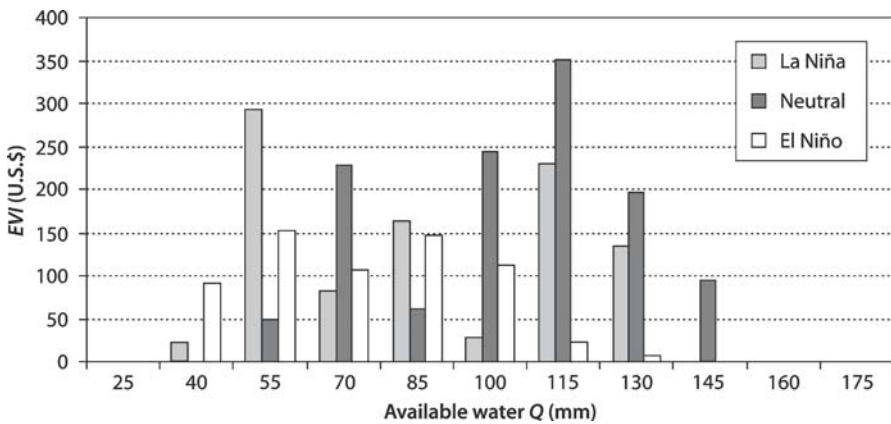


Fig. 9.1. Expected value of information (U.S. dollars) for different levels of available water and El Niño phases in the growing period

ter using El Niño forecasts and the one that bases his decision on historical ET_c values. Figure 9.2 shows this situation for a situation where available water was 55 mm. Because perfect knowledge of El Niño phases is assumed, the objective function using El Niño forecasts does not change with time. During La Niña years (Fig. 9.2a) EVI decreases as a consequence of a revised optimization. As time progresses much of the final outcome is already determined, and the corrections made in water allocation reduce the relevance of climate forecasts. For normal years (Fig. 9.2b) the situation is different, since ET_c in these years is higher than the climatological average, the misinterpretation of future ET_c values is carried out, and even though some adjustment can be made, EVI remains close to the initial values.

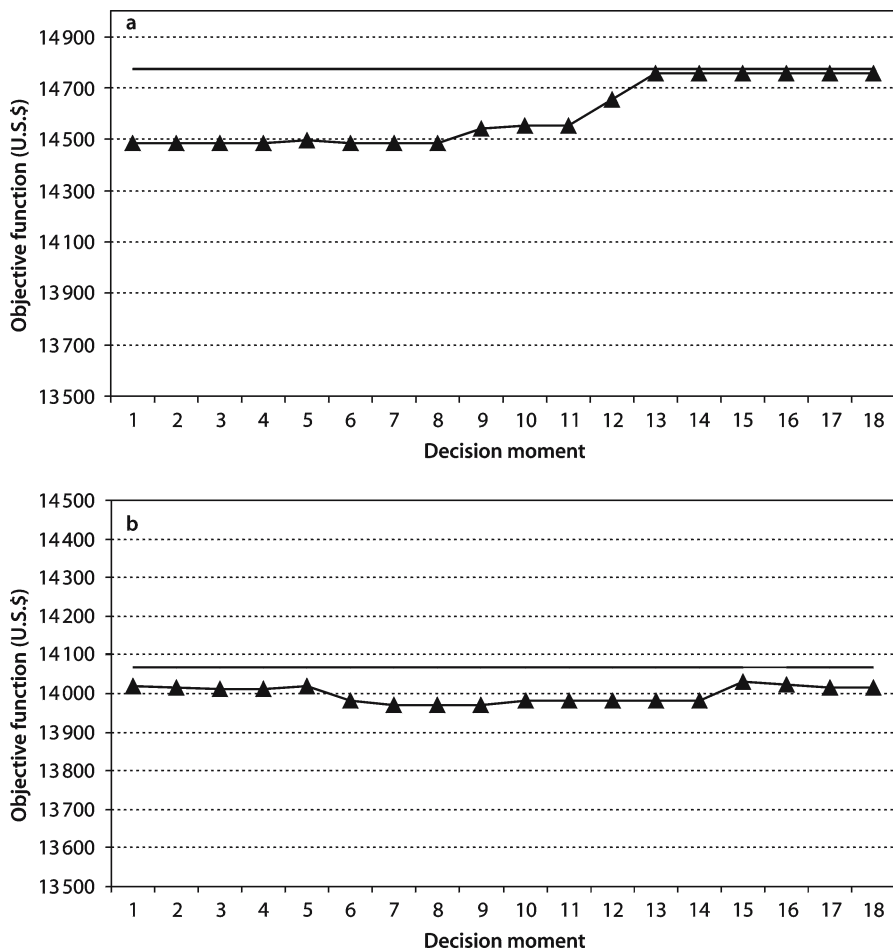


Fig. 9.2. Objective function of a decision-maker that allocates water using El Niño-driven climate forecasts (straight line) and a decision-maker that uses climatological values but updates the objective function considering observed ET_c values (line with triangles); a results for La Niña years; b results for normal years

Given the results obtained in this work, it is concluded that: (1) In locations where ENSO signal has an effect on water demands (for instance central Chile) there is an economic potential for the use of climate forecasts on water resources allocation at the farm level, (2) The expected value of information is not a monotonic function because when water is very scarce allocation decisions are limited, (3) In some situations wrong estimations of future ET_c conditions can be corrected but the time dependence nature of the system makes advisable to incorporate information as a tool for irrigation management.

The results of this work correspond to a preliminary assessment of *EVI*. The results strongly depend on yield model representations. In this case Jensen's model only represents yield variability as a consequence of a difference between actual and potential evapotranspiration and the same final outcome would be achieved in all El Niño phases if water was not a limiting factor. The use of more sophisticated weather driven crop simulation models, as a tool to refine yield forecasts, will probably produce better estimates of the consequences, and allow the decision-maker to capture a higher proportion of the additional economic benefits associated to climate information.

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Towards the Development of a Spatial Decision Support System (SDSS) for the Application of Climate Forecasts in Uruguayan Rice Production Sector

A. Roel · W. E. Baethgen

10.1 Introduction

Recent scientific advancements are improving the ability to predict some major elements of climate variability, in advance of the crop-growing season. In selected regions of the world, climate anomalies are linked to the onset and intensity of a warm or cold event of the El Niño-Southern Oscillation (ENSO) phenomenon. Southeast of South America is within the regions of influence of this phenomenon (Ropelewski and Halpert 1989). Hence seasonal weather and climate fluctuations have significant economical impacts on the agricultural production sector of this region.

More recent studies conducted in southeastern South America revealed the existence of a near symmetry between impacts of El Niño and La Niña on precipitation as well as on non-irrigated crop productivity. Positive rainfall anomalies prevail in El Niño years, and negative rainfall anomalies prevail in La Niña years, during the austral spring and/or summer months (Baethgen 1997; Baethgen and Giménez 2002).

While there has been much written about impacts of climate variability, there has been relatively little done in relation to applying knowledge of inherently imprecise climate predictions to modify actions ahead of likely impacts, i.e. applications of climate predictions. Although forecasts make predictions of climate variable behaviors for large regions of the world, these regions are not uniform. Hence in many situations in some areas of these regions forecast recommendations were suitable while in others they were not. A pilot project was then proposed to evolve a system for the effective application of a seasonal climate forecast, which can address the natural spatial variability in growing conditions that control productivity in a rice ecosystem in Uruguay.

Therefore the objectives of this study were: (1) evaluate ENSO effects on Uruguayan rice production; (2) evaluate the capability of crop simulation models in recreating the observed yield spatial variability; and (3) simulate rice yield spatial variability under different seasonal forecast scenarios: El Niño, La Niña and neutral years.

10.2 Materials and Methods

In this study, the relationship between ENSO 3.4 average total sea surface temperatures (SST) anomalies in October, November and December (OND) and rice yield have been analyzed to evaluate ENSO effects on Uruguayan rice production. Yield data were obtained from the Uruguayan Rice Growers Association (ACA). Yields for any given year were expressed as the relative difference between the observed yield for that year and the yield predicted by the regression model (Eq. 10.1):

$$RYD = (Yld(n) - PYld(n)) \cdot 100 / PYld(n) \quad (10.1)$$

where, RYD = relative yield deviation expressed in (%), $Yld(n)$ = observed crop yield for year n , and $PYld(n)$ = yield predicted by regression model for year n .

SST anomalies were obtained from the Climate Prediction Center of NOAA. The anomalies were calculated relative to the period 1950–2003 and aggregated into three-month period means. Rice is normally planted during October–November and harvested during the end of March through May. Therefore any possible relationships found during OND may have significant forecasting applications for this crop.

The study was conducted at a 12 ha rice field located at El Paso de la Laguna Experimental Unit of the National Institute of Agricultural Research (INIA), Uruguay. The cultivar used was El Paso 144 and the planting date was 7–8 November 2002. Seeding rate was 190 kg ha⁻¹. Rice was direct seeded on dry soil. Fertilizer applications were: 170 kg ha⁻¹ 15-35-15 (N-P-K) at planting followed by 50 kg ha⁻¹ of urea at flooding time (30 days after emergence) and 50 kg ha⁻¹ of urea at panicle initiation.

Ten locations were selected in this 12 ha rice field in which recording data loggers (Hobo H8 Pro) were fitted. These loggers have an internal temperature sensor that measures ambient air temperature, in this situation representative of canopy temperature, and an external sensor that was used to measure water temperature. The loggers were attached to stakes placed vertically in the field, with the external sensors placed approximately 0.05 m below field water level. As the rice grew, the internal sensors were moved upward along the stake so that they were always near the top of the canopy. Water and canopy temperatures were measured hourly throughout the growing season. Data logger locations were georeferenced using a back-pack differential global positioning systems (DGPS) receiver (Trimble AG 132).

Daily rainfall, temperature and solar radiation data were obtained from the Agrometeorological Weather Station located at El Paso de la Laguna Experimental Unit of the INIA for the period 1973–2003.

At harvest, yield, yield components, and percent blanking were recorded in the vicinity of each sensor. Sensors were removed before harvest. A sample plot (2.5 m × 3.5 m) was harvested with an experimental plot combine at each sensor location. Yields standardized to 14% moisture content were measured. Interpolated yield maps of the field were created using a geographic information system (Arcview, ESRI, Redlands, CA). Yield data from each of the ten locations were spatially interpolated to a fixed 5 m × 5 m grid using inverse distance weighted interpolation with power 2 and number of neighbors 12.

Soil samples were extracted at three different depths: 0–10 cm, 10–20 cm and 20–30 cm at the same locations where sensors were installed. Yield was predicted at each sensor locations using the DSSAT v3.5 CERES-Rice model.

10.3

Results and Discussion

10.3.1

ENSO Effects on Uruguayan Rice Production

The fact that rice is irrigated under Uruguayan conditions theoretically should ameliorate ENSO effects on this crop productivity. Straightforward reasoning will indi-

cate that for an irrigated crop like rice, ENSO phases can have opposite effects than in non-irrigated ones.

Figure 10.1 shows national rice yield average evolution in the last 31 growing seasons (1972–2003). In order to analyze ENSO impacts on rice production the probabilistic impact of ENSO phases on the distribution shifts of crop yields were studied using the same approach as the one used by Baethgen. The detrended national yield crop average data from 1973 to 2003 were divided into quartiles and any given value was defined as being “high” if it was greater than the third quartile (upper 75% of the data), “low” if it was less than the first quartile (lower 25%), and “normal” if its value fell between the first and the third quartile (central 50% of the data). By this way the range of average yield values that corresponded to each quartile were determined. Using these values the shift in the distribution of crop yields were studied for the different ENSO phases (El Niño, La Niña and neutral). The IRI classification of El Niño, neutral and La Niña years was used (<http://iri.columbia.edu/climate/ENSO/enso.html>).

Table 10.1 shows the classification of the series of years according to ENSO phases. This analysis showed that the distribution of national relative yield differences (RYD) varied with ENSO phases (Fig. 10.2). For example, the frequency of high rice yield differences was more than two times higher in La Niña years than in neutral years. On the other hand in El Niño years the chances of having high yields were zero. In summary this figure clearly shows that in La Niña years the chance of having high yields increased with respect to the neutral years, while in El Niño years this chance strictly does not exist.

10.3.2 Spatial Variability

The DSSAT v3.5 rice model requires information about: weather (temperature and solar radiation), soil variables, genetic coefficients and crop management. Crop manage-

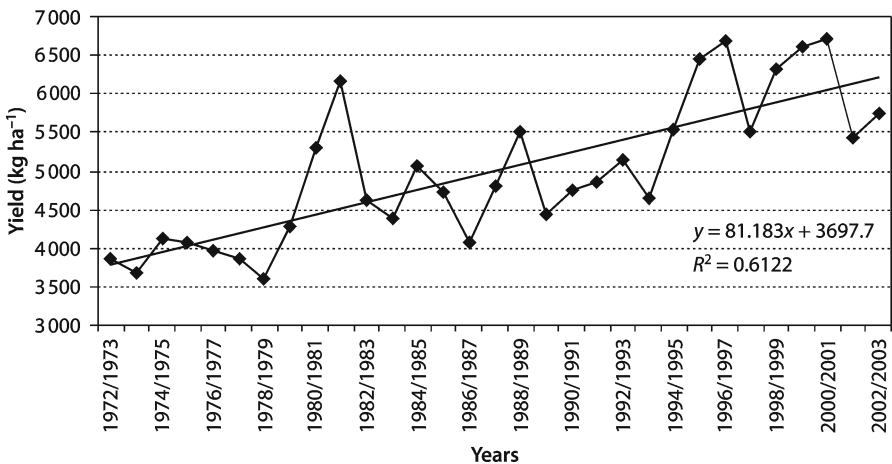
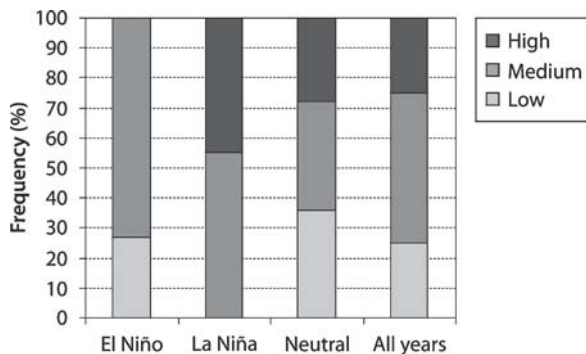


Fig. 10.1. National rice yield (1972–2002)

Table 10.1. El Niño, La Niña and neutral years

El Niño	Year	La Niña	Year	Neutral	Year
1972–1973	1	1973–1974	1	1978–1979	1
1976–1977	2	1974–1975	2	1979–1980	2
1977–1978	3	1975–1976	3	1980–1981	3
1982–1983	4	1984–1985	4	1981–1982	4
1986–1987	5	1988–1989	5	1983–1984	5
1987–1988	6	1995–1996	6	1985–1986	6
1990–1991	7	1998–1999	7	1989–1990	7
1991–1992	8	1999–2000	8	1993–1994	8
1992–1993	9	2000–2001	9	1996–1997	9
1994–1995	10			2001–2002	10
1997–1998	11			2002–2003	11

Fig. 10.2. National rice yield distribution and ENSO phases (1972–2003)



ment and genetic coefficients were uniform for the field since the same cultivar and management practices were applied throughout the studied field. In order to assess the capability of the model in recreating the observed rice yield spatial variability, three different simulations were carried out at each sensor location:

Simulation 1. Weather information (temperature and solar radiation) was extracted from the agrometeorological weather station located at INIA. Soil information was gathered from the soil analyses data that come from the samples extracted at each sensor location. In these simulations all locations have the same weather data but differ in the soil variables data.

Simulation 2. Same as above, but the temperature from the weather station was substituted with each canopy temperature’s data registered at each sensor locations. In these simulations each location had its own temperature and soil data and shared the solar radiation data extracted from the weather station.

Simulation 3. Same as Simulation 2, but temperature from the weather station, was substituted with each water temperature data registered at each sensor locations.

Table 10.2 displays the correlation values between observed and simulated yields for all three simulations. Figure 10.3 displays the observed and interpolated predicted yield values for all simulations. In these figures, it can be observed that the crop simulation model was able to capture satisfactorily the spatial variability that was measured in the field. It is important to highlight in these figures that the actual observed spatial variation in yield ranges from 5 000 to 7 100 kg ha⁻¹ (2 100 kg), while the predicted ones vary in general from 4 000–5 250 kg ha⁻¹. This indicates that the model tends to underestimate productivity under these conditions and that the observed spatial variability was indeed larger than what was predicted. The reason for this underprediction should be further investigated.

Table 10.2. Correlation between observed and predicted yield values

Simulation no.	Correlation with observed yield
1	0.80 ^a
2	0.78 ^a
3	0.90 ^a

^a $P = 0.0001$.

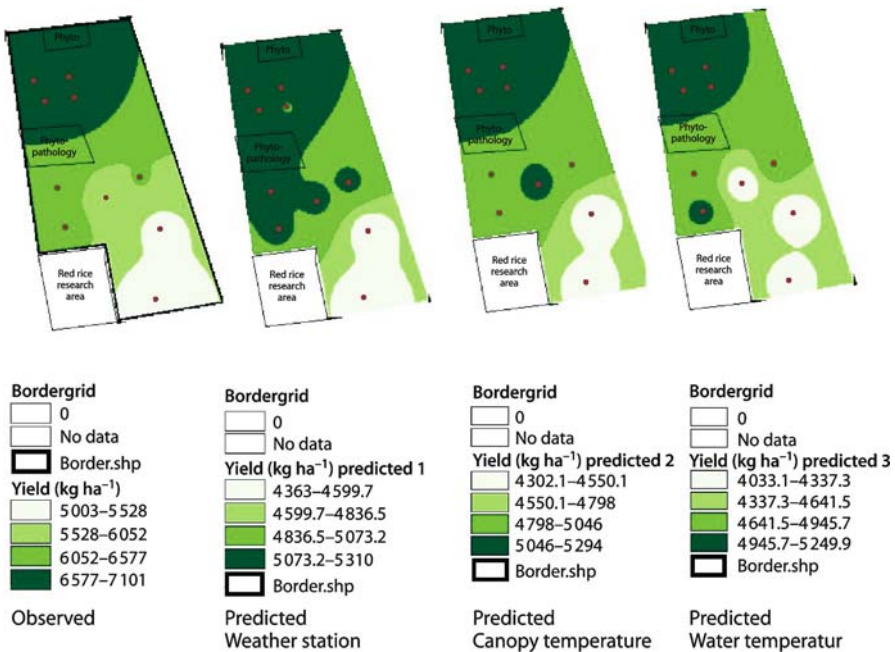


Fig. 10.3. Observed and predicted yield spatial variability for simulations 1–3

10.3.3 Temporal Variability

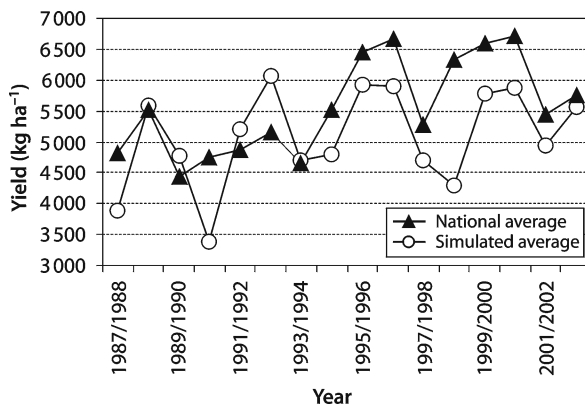
In order to achieve this, the average simulated yields of the 10 selected locations in the field were compared with the country's national rice yield average evolution in the last 16 growing seasons (1987–1988 to 2002–2003) (Fig. 10.4). For each growing season, the national rice yield average is determined by a large number of environmental situations (i.e. planting dates, fertilization, soils, cultivars, etc.). Differences among growing seasons are caused in part by the differences in the “average” climatic conditions of each growing season. In other words, each growing season can be classified as good or bad from the climatic point of view. The goal of this section of the study was to test if the model was able to capture those good, fair and bad years.

Overall the DSSAT v3.5 CERES-Rice model was able to capture satisfactorily rice yield temporal variability. The model was able to simulate higher or lower production levels in “good” or “bad” growing seasons. The only exceptions of the latter are in the 1990–1991 and 1998–1999 growing seasons when the model determined average yields for the field for these years were lower than in the previous seasons (1989–1990 and 1997–1998) when the national yield averages actually increased during these years with respect to the previous ones.

10.3.4 Spatiotemporal Variability

The model was run, in each of the ten selected locations in the field using the weather data from a series of years (1972–2003) to characterize the spatiotemporal variability. The same soil data, management practices (planting date, seeding rate, fertilization, etc.) and genetic data (El Paso 144) that were used in the studied field for 2002–2003 growing season were applied at each of the ten locations through out all of these years. Specific attention was given to evaluating if different regions within the studied field would react differentially to a given climatic data. Simulated yield data from each of the ten locations and for each 31 growing seasons were spatially interpolated in order to generate yield maps for each growing seasons. Figure 10.5 shows the set of yield maps

Fig. 10.4. National vs. simulated yields



from the 1972–1973 through the 2002–2003 growing seasons. In order to be able to display the yield range variability along these 31 growing seasons with a common legend, the whole data set of yield outcomes were and divided into quartiles. These quartiles defined the range of variability of the different yield classes displayed in Fig. 10.5.

Figure 10.5 also categorizes each growing season according to ENSO conditions (El Niño, La Niña and neutral conditions, Table 10.1). This figure shows that in all the growing seasons in which some part of the field presented production levels that fell in the lowest yield class ($2\,968\text{--}3\,819\text{ kg ha}^{-1}$, red color), those years corresponded to El Niño years (1986–1987, 1987–1988 and 1990–1991). Conversely in all the years classified as La Niña, the yield variation of the field tended to be in the highest yield classes (green and blue) with the exception of the 1998–1999 and 1974–1975 growing seasons. These results coincide with the previous ones suggesting that La Niña year's climatic conditions are better for rice production.

10.4 Conclusions

The availability of new technologies like yield monitors, yield mapping software, GPS, satellite and aerial images and GIS has made possible to measure crop growing conditions as well as grain yield within a field at a very high spatial resolution, allowing very fine and precise description of the spatial variability (Roel and Plant 2004). A number of research groups around the globe are seeking to apply seasonal climate forecasts to improve management of food production systems and security of farmer livelihood in the face of climatic risk. One of the tools frequently employed by these efforts is dynamic crop simulation models (Hansen 2000). In this study we integrate this tool with the mentioned advancements regarding the capability of a precise description of yield spatial variability. We consider that this integration may increase the possibility to evaluate the application of seasonal climate forecasts at a regional scale. This integration will allow to study if in fact regions within the scale at which climate prediction model output are given, react uniformly to different climatic conditions. Consequently, evaluations can be made as to whether uniform recommendations can be made from a given forecast or if certain areas within the scale of the forecast should be treated differently.

This study showed that the distribution of national rice yield averages varied with ENSO phases (Fig. 10.2). The frequency of high national rice yields average was more than two times higher in La Niña years than in neutral years. The study conducted in the 12 ha rice field showed that this field presented certain yield spatial pattern with high yielding areas at the north and center portion of the field and a low yielding areas at the south portion of the field. The DSSAT v3.5 CERES-Rice model showed to be able to capture satisfactorily rice yield variability at the spatial and temporal levels. When the model was run spatially, at the different locations within the field and temporally along the different growing seasons, the same pattern of low yield spatial variation can be observed in the southern part of the field. Overall, this suggests that there is no interaction between temporal and spatial effects, there were no climatic conditions (temporal variability) that can make that the south portion of the field achieve a higher yield than the northern portion.

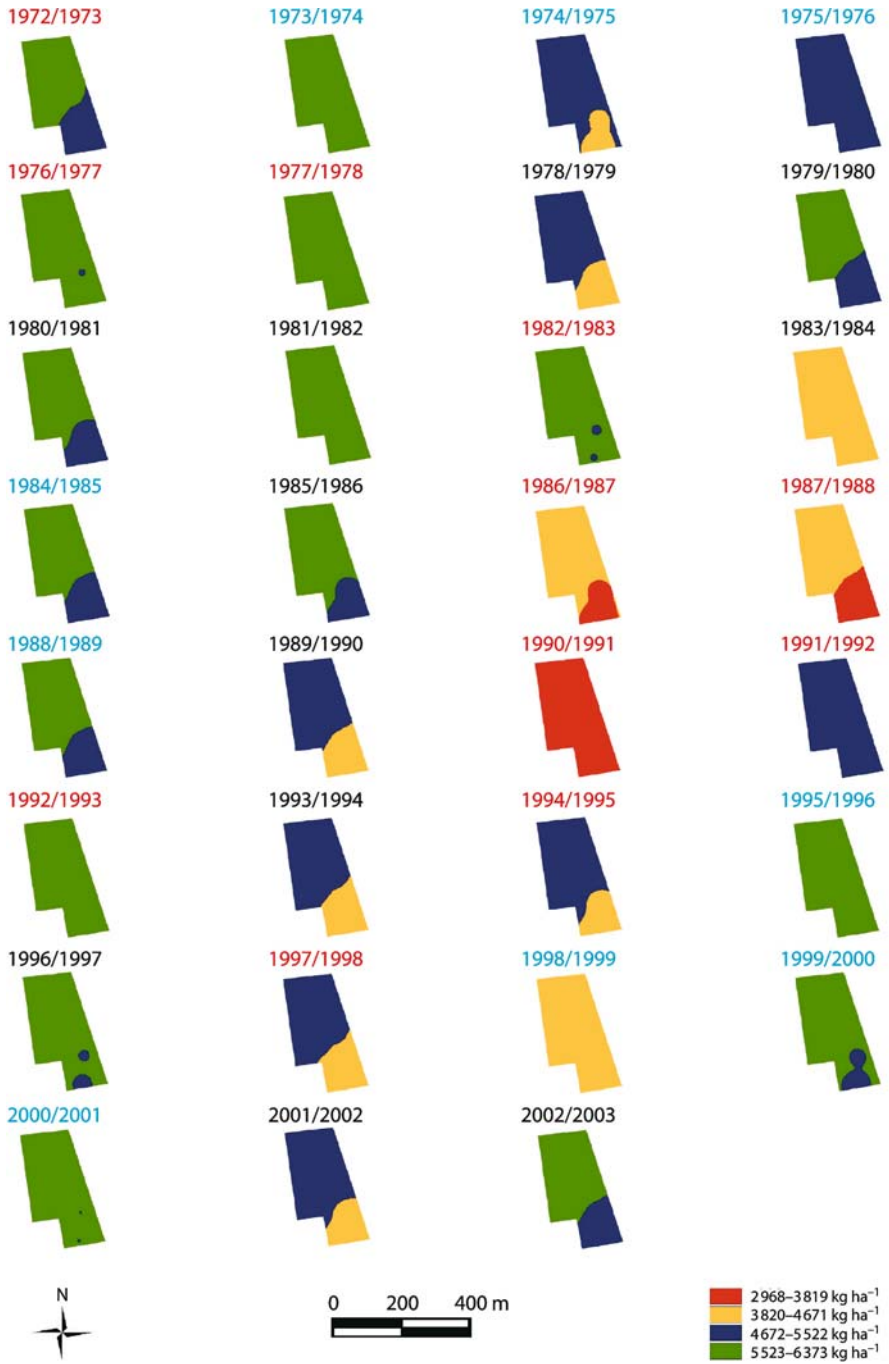


Fig. 10.5. Yield spatial variability; red years correspond to El Niño, blue years correspond to La Niña and black years to neutral conditions

The chief difficulty in linking climate forecasts scenarios with crop simulation models is the substantial mismatch between the forecast output spatial and temporal scales and crop simulation model input requirements. This study was able to demonstrate that for this rice field although we were able to characterize its yield spatial variability very precisely this pattern of spatial variability did not change with different climatic conditions. Therefore, yield spatial variability within this field seems to be regulated by factors related to the soil and not with the climatic conditions. Consequently, at the scale of this field forecast output scale did not constitute a problem. We believe that the approach used in this study can be implemented at a larger spatial scale to evaluate at which level of spatial resolution forecast output scale starts to become a problem.

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Assessing the Use of Seasonal Climate Forecasts to Support Farmers in the Andean Highlands

G. A. Baigorria

11.1 Introduction

Andean farmers plant their fields before and during the initial months of the rainy season, avoiding planting all of their fields on a specific date or with the same crop. This traditional technique reduces climatic risks that occur as a result of the high interannual climate variability and also assures a minimum production for self-consumption during years of poor production. Farmers make decisions according to their expectation and based on previous experiences of risk and they have developed their own systems for weather and seasonal climate forecasting based on meteorological and astronomical phenomena as well as biological behavior of wild species (Baigorria 2005). However, in comparison to other Andean areas, studies in La Encañada and Tambomayo show that these indicators are more related to short-term decision-making such as when to apply agro-chemicals, than what, when, where and how to plant and crop. Although formal weather and seasonal climate forecasts are available from the Peruvian National Service of Meteorology and Hydrology, these are used only in a few cases, due to the inadequate spatial resolution and the lack of training to interpret them properly. Similarly, but at a different level, the extension offices provide general-purpose recommendations without using these forecasts.

In the present case study, the translation of a seasonal climate forecast from global circulation models into a map with the optimal planting dates for different crops was performed. This required downscaling of the forecasts and applying crop growth simulation models to evaluate the impact of expected seasonal-climate conditions and crop management on crop yields. These models increased the value of the seasonal climate forecasts, making available this kind of information in appropriate agricultural terms to stakeholders not deeply involved in climatology.

11.2 Data and Methods

11.2.1 Study Area

The present case study was performed in the Andean Highlands of Peru in the watersheds of La Encañada and Tambomayo, Cajamarca (Fig. 11.1).

The 165 km² total area ranges in altitude from 2 950 to 4 000 m above sea level (a.s.l.). According to the soil taxonomy (USDA-NRCS 1998), soils are classified as Entisols,

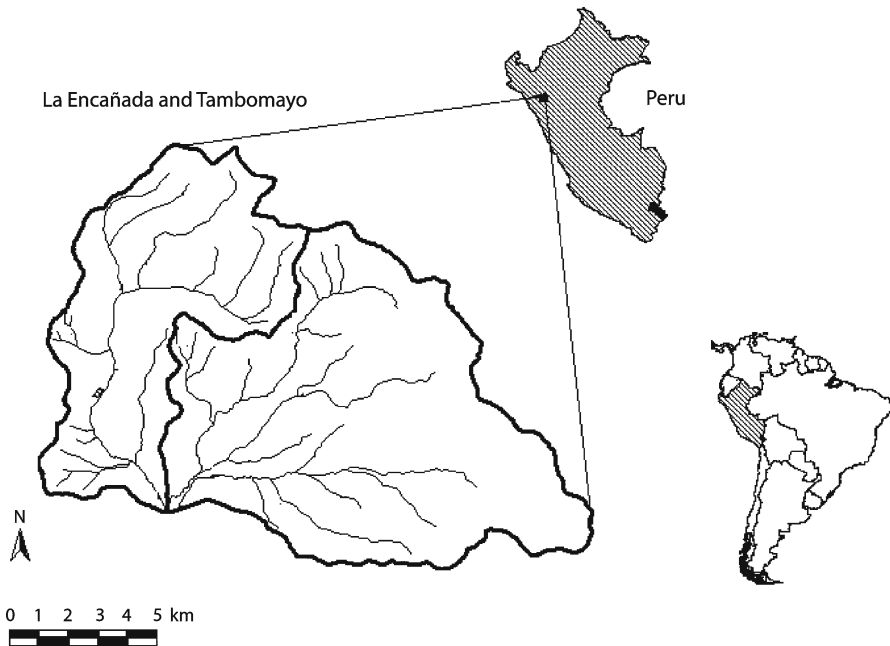


Fig. 11.1. Location map of La Encañada and Tambomayo watersheds

Inceptisols and Mollisols. Production systems are mainly based on natural and improved pastures and crops, basically Andean roots and tubers such as potato, oca (*Oxalis tuberosa*), ulluco (*Ullucus tuberosus*) and maca (*Lepidium meyenii*), as well as grains like barley and wheat (Tapia 1995). Agriculture is marginal and it is located on steep hillsides up to 65% slope (Romero and Stroosnijder 2001). Annual income per ha ranges from U.S.\$400 to U.S.\$3 200 (Valdivia 2002) and per capita income is usually less than U.S.\$1 per day (Baigorria et al. 2002). According to Peruvian government statistics, despite the presence of gold mine explorations in the area, Cajamarca is considered one of the most economically depressed areas in Peru.

Three weather stations are located in the study area: La Toma ($7^{\circ}3.72' S$; $78^{\circ}16.92' W$; 3 590 m a.s.l.), Usnio ($7^{\circ}5.34' S$; $78^{\circ}18.96' W$; 3 260 m a.s.l.) and Manzanas ($7^{\circ}7.08' S$; $78^{\circ}18.60' W$; 3 020 m a.s.l.) with an historical record of 10, 22 and 10 years respectively. According to Tapia (1995), these three weather stations divide the watersheds into three agroclimatic zones (ACZ) denominated as highlands, hillside and valley respectively.

11.2.2

Field Survey

Eight participative stakeholder workshops involving 339 farmers were held several months before the incoming cropping season (September 2003–May 2004). The goal was to obtain detailed information about usual farm management practices includ-

ing crops, N-fertilization ranges and planting dates as well as plans for the next cropping season. The workshops were performed in different areas according to the hamlet boundaries as well as the varied access to infrastructure and natural resources. Baigorria (2005) described other relevant information concerning local weather and seasonal climate forecast indicators currently in use by farmers, factors influencing crop decisions and the current use of formal forecast by decision-makers.

11.2.3

Sea Surface Temperature Data

Two different kinds of SST data were used in the study in order to: first, calibrate and validate the downscaling models and second, to downscale the seasonal climate forecast.

11.2.3.1

Monthly Historical Records

Time series of observed SST maps (pixel size of 2° latitude by 2° longitude) provided by the National Center for Atmospheric Research and the University Corporation for Atmospheric Research (NCAR-UCAR) were used to develop the downscaling models.

11.2.3.2

Seasonal Climate Forecasts

Monthly forecast maps of SSTs for a three-month moving average with a pixel size of 2° latitude by 1.5° longitude were used as inputs in the application of the downscaling models. Data were provided by the Environmental Modeling Center - National Oceanic and Atmospheric Administration (EMC-NOAA).

11.2.4

Spatial and Temporal Downscaling

Several steps were performed to finally obtain the daily forecast values of minimum and maximum temperature, rainfall and incoming solar radiation. These steps involve: first, both spatial and temporal downscaling from three-month moving average SST forecast to monthly forecast of the meteorological variables at weather station level; and second, at this level, temporal disaggregation from monthly to daily values.

11.2.4.1

Development Validation and Application of Downscaling Models

Because historical records and forecasts of SSTs have different spatial resolutions and temporal step intervals, a process to standardize the data was performed. Forecast maps were re-sampled to a pixel size of 2° latitude by 2° longitude using a weighted distance interpolation method (Isaaks and Srivastava 1989) and the observed SST were temporally aggregated as a three-month moving average series. Using the software

CLIMLAB2000 (Tourre 2000), the monthly time-series of minimum and maximum temperatures, and rainfall from each weather station were correlated with each pixel from the observed three-month average SST maps. The results were monthly maps of correlation indexes between SST and weather conditions with a three month lag (i.e. SST in July–September vs. maximum temperature in October). Areas with similar correlation indexes were selected visually from each correlation map, and all the values belonging to this area were averaged giving as a result only one value of SST representing the area. All of these average values fed a stepwise multiple regression analysis ($\alpha = 0.05$) against monthly values of minimum and maximum temperatures, and rainfall. Two-third of the historical records were used to develop the downscaling models, while the remaining data were used for validation.

After evaluating the downscaling models performance during validation, the algorithms obtained from the multiple regression analysis were fed with the monthly three-month moving average forecasts. Finally, monthly forecast of the three meteorological variables at each weather station were obtained.

11.2.4.2

Daily Disaggregation of Monthly Forecast

Because the crop models used in this research needed daily data, a weather generator WGEN (Richardson and Wright 1984) was used to downscale the monthly forecasts. To reduce the uncertainty produced by the effect of statistically simulating weather from seasonal-climate (e.g. frost or rainfall frequencies), 99 realizations of WGEN yielded 99 files of daily data. Afterwards, incoming solar radiation was estimated by the Bristow and Campbell (1984) model, previously calibrated and validated for the region by Baigorria et al. (2004).

11.2.5

Geospatial Modeling

GIS and Biophysical Modeling Laboratory – GABP-Lab (Baigorria et al. 2001) spatially integrates the capabilities of geographical information systems and several process-based crop models involved in the Decision Support System for Agrotechnology Transfer – DSSAT (Jones et al. 1998). The crop models used in the present study were SUBSTOR-Potato (Ritchie et al. 1995) and CERES-Cereal model (Singh et al. 1991) previously calibrated to the Andean conditions (Bowen et al. 1999; Quiroz et al. 2003; Stoorvogel et al. 2004).

Using the 99 weather files generated by WGEN, 99 realizations of potato, wheat and barley were performed under each of the different management strategies given as a result of the field surveys, for each pixel in the map. For each pixel and each management strategy, the average and the standard deviation from the 99 realizations were calculated, giving as a result, optimal planting date maps for each crop as well as risk maps associated to each management strategy alternative. Risk maps were presented as maps of percentage of coefficient of variation, dividing the standard deviation by the average. The maps were printed and disseminated among the farmers of La Encañada and Tambomayo.

11.3 Results and Discussion

11.3.1 Field Survey

Farmers from La Encañada and Tambomayo watersheds mainly distribute their crops in two seasons based on the availability of rainfall. Table 11.1 summarizes the crop and management strategies identified as a result of the eight participative stakeholder workshops.

These management strategies were used as input in the realizations of GABP-Lab, thus generating yield forecast maps to the entire possible combinations: crop \times planting date \times N-fertilization rate.

11.3.2 Spatial and Temporal Downscaling

Figure 11.2 shows the performance of the downscaling models at the time of calibration. According to the multiple regression models, minimum and maximum temperatures, as well as rainfall, were expected to be close to normal conditions during this cropping season. This prediction was confirmed by the seasonal climate forecast made in December 2003 (during the study) by the International Research Institute of Climate Prediction.

Table 11.1. Identified management scenarios for the upcoming wet cropping season

Crops	Planting date	N-fertilization (kg ha ⁻¹)
Potato	October to December	25 to 100
Wheat	November to January	20 to 80
Barley	November to January	20 to 80

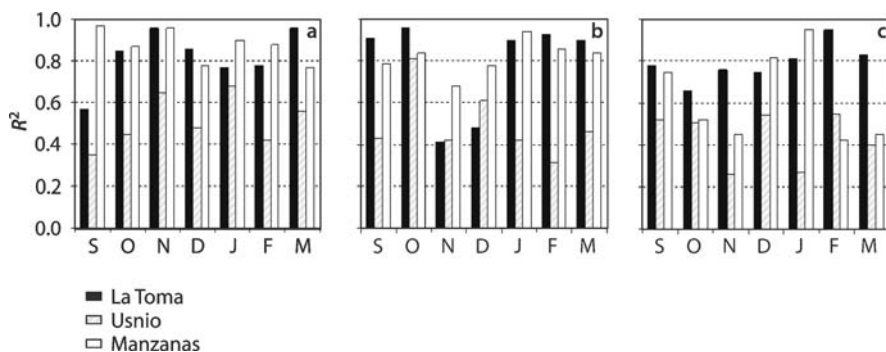


Fig. 11.2. Monthly coefficient of determination for the three weather stations La Toma, Usnio and Manzanas; **a** maximum temperature; **b** minimum temperature; **c** rainfall

During the validation process, the residuals (difference between forecasted and observed data) were analyzed to detect patterns in the errors. Figure 11.3 shows the tercile probabilities of the residuals using the remainder one-third of the years of the

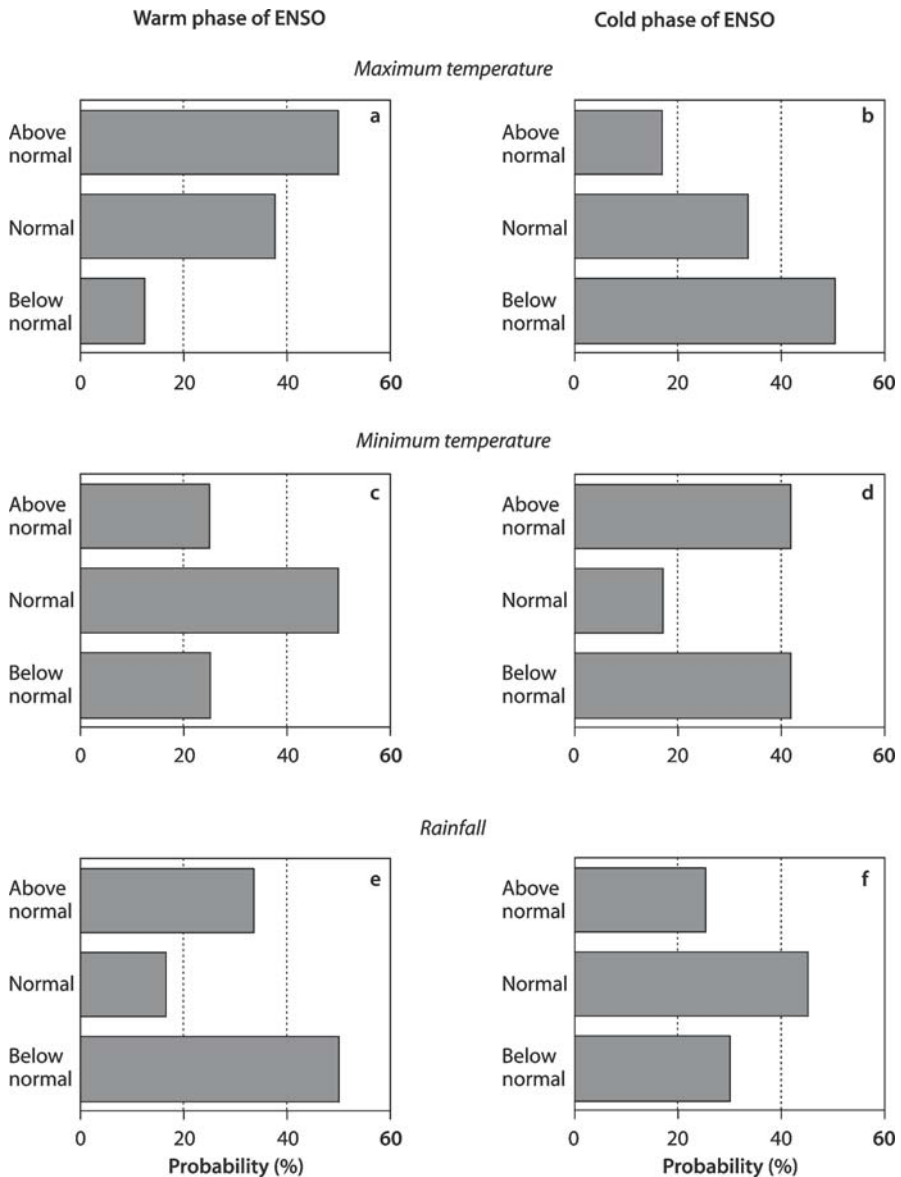


Fig. 11.3. Tercile probabilities of the residuals at the time of validation during warm phase of ENSO (a, c, and e) and the cold phase of ENSO (b, d, and f) respectively. Variables correspond to (a, b) maximum temperature, (c, d) minimum temperature, and (e, f) rainfall

historical record. Because of a heterogeneous distribution of the residuals, these values were disaggregated according to the phases of El Niño and the Southern Oscillation Index (ENSO) in order to analyze the ENSO-phase effects in the performance of the downscaling models. This analysis suggested that the developed multiple regression models are quite appropriate for normal years, however, the models underestimate the maximum temperature during the El Niño phase and overestimate during the La Niña phase. In the case of minimum temperature, the tercile probabilities show that residuals are well distributed during El Niño; however, during La Niña the tercile probabilities of the residuals demonstrate a large noise in the predicted values. In the case of rainfall, results show that during El Niño the multiple regression models produce the largest noise.

It is necessary to explore multiple regression models in a more dynamic way and based on a physical explanation of the involved process. Results obtained in the presented research using a more empirical approach of the multiple regression models indicate the necessity of in-depth analysis, whether to generate multiple regression models in general climatic terms as the presented here or multiple regression models to normal conditions and to each specific extreme meteorological event. Regional numerical climate models involving physical explanation can better represent a total variety of meteorological behavior of an entire area.

The downscaling process presented here is based on the forecasted monthly averages values of the three meteorological variables. However, the corresponding variability during a specific month, characterized by weather generators as the standard deviation, rainfall distribution scale parameter and the probability of dry-wet sequences (Richardson and Wright 1984) were applied without variation. Romero and Baigorria (2005) demonstrated that the variability of rainfall in La Encañada and Tambomayo watersheds is affected seriously during El Niño and La Niña events. Thus, new approaches in weather generators conditioning variability based on ENSO-phase can decrease the uncertainty during the temporal downscaling (Grondona et al. 2000). Because close-to-normal conditions were predicted, this approach was not applied.

11.3.3

Geospatial Modeling

Yield forecast maps under different scenarios of crop production (Fig. 11.4) support farmers to interpret the effects of the formal seasonal climate forecast on their lands under their own different previously planned crop management options. Risk maps (Fig. 11.5) support farmers with quantitative information about the risk of each crop management scenario under the seasonal climate forecasted conditions. Thus, both low-yield fields and high-yield fields can be related to a low or high percent of coefficient of variation. Farmers with the highest economic portfolios can rent lands with better response to N-fertilization and lower risk. High-yield fields with a high risk typically have investments of valuable crops and N-fertilization, according to the risk preferences or risk aversion of the owners. However, in low-yield fields, often related to marginal areas or natural pastures opened as new crop-field, yield forecasts support the poorest farmers to make better investments of the low resources they have in an attempt to assure food security.

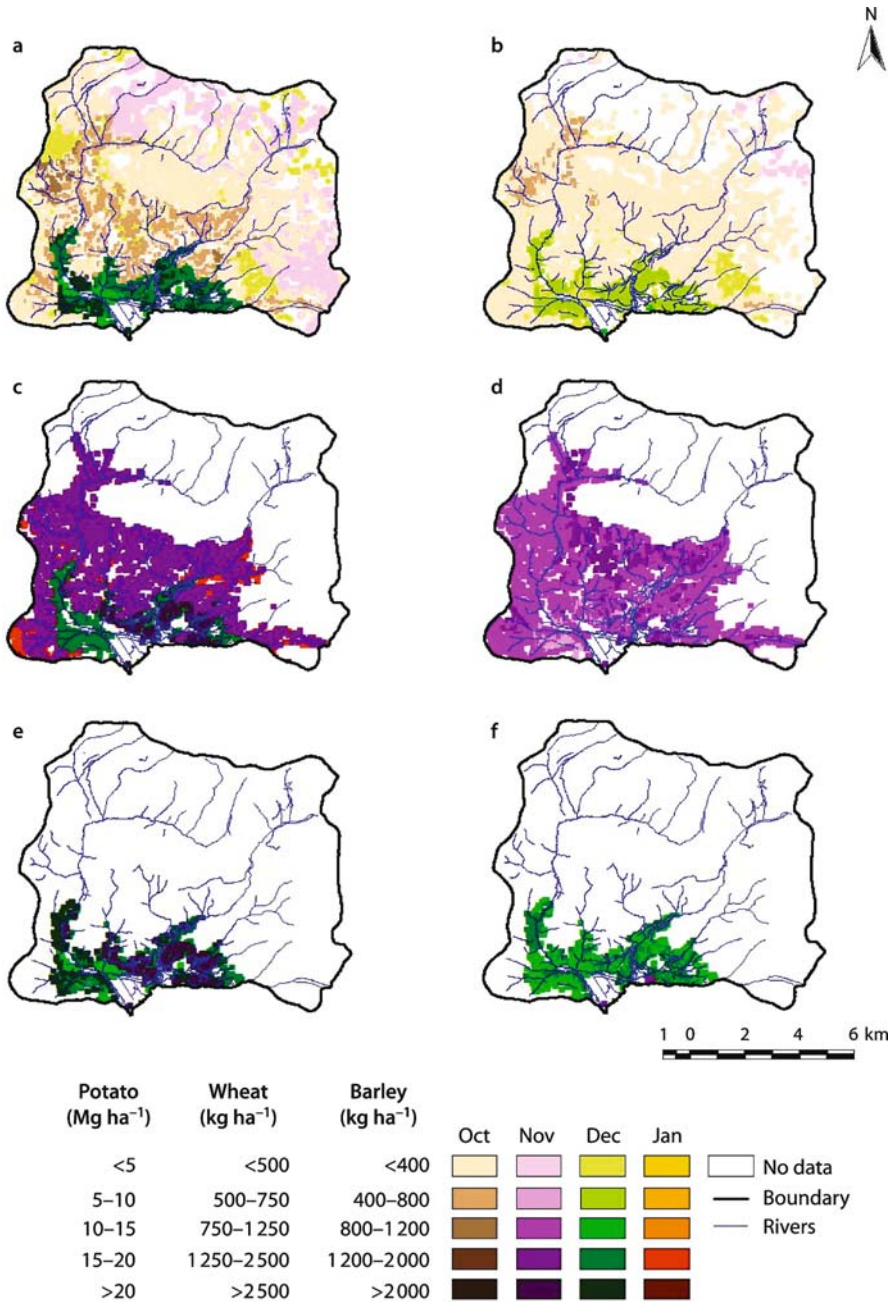
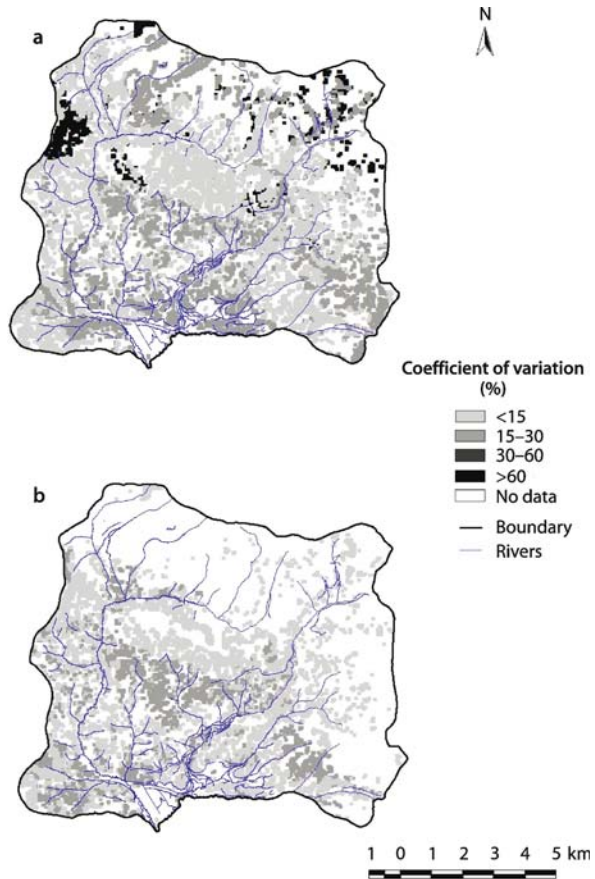


Fig. 11.4. Optimal planting date maps of potato, wheat and barley under high and low N-fertilization levels; a potato - high N; b potato - low N; c wheat - high N; d wheat - low N; e barley - high N; f barley - low N

Fig. 11.5. Maps of percentage of coefficient of variation of potato yield under different levels of N fertilization; **a** high; **b** low



With the resulting maps on hand, the next step was to make them available to the farmers. After a training process, farmers understood how to use the maps (same as presented in Figs. 11.4 and 11.5), and they began to interpret the yield forecast in the areas corresponding to their own fields to analyze the feasibility of the information and more rapidly incorporate the information into their own conceptual models. The first observed response from farmers at the time of information dissemination was a desire to increase the percentage of planting area within the optimal proposed planting date, attempting to take advantage of the yield forecast. However, the farmers never wanted to risk the entire planting area, neither in a single planting date nor for only one crop. Also notable was that only a small percentage of farmers considered changing the pre-determined crop, despite the fact that the information was disseminated one month before the first evaluated planting-date. In this way, adoption of the findings by farmers would finally depend on the destination of their harvest products, which varies according to the hamlet, crop, economic portfolio and farmer's risk preferences and aversions. However, best crop yields are not necessarily related to the high-

est profits, especially in hamlets that depend more on markets. Thus, the use of this information is to translate forecasts to support decision-making and not to make the actual decision.

The key point of this study is the possibility of linking the time-dimension, dominated by climate during a cropping season, with the spatial-dimension, dominated by soils and microclimates. Another key point is the possibility of translating global seasonal climate forecasts derived from temperature anomalies in °C to crop production in $t\ ha^{-1}$; from science language to farm language. The interdisciplinary approach presented here provides support to allow better tactical decisions to be made under different land use management scenarios performed by farmers. However, farmers need time to incorporate the new information in their decision frameworks.

Farmers already have experienced the use of seasonal climate forecasts by using ancestral knowledge. However, sometimes their local indicators predict a totally opposite behavior of the next season-climate than that predicted by the scientific community. Two possible explanations exist: (i) errors in the forecasting models; and/or (ii) decreasing accuracy of the local indicators due to externalities, as for instance climate change, new access to irrigation systems (Quiroz et al. 2003) or pollution. Forecasting models are improved year-by-year while local indicators will adapt to the new conditions at a slower pace. Therefore, it is important that local forecasters keep up and learn to read the national and regional forecasts instead of only relying on the local indicators. Translated seasonal yield forecast information must be taken as one of the many components of the system and not as sole source of information. Feedback from stakeholders on the research and scales are as important as knowing how to incorporate risk into the decision-making framework.

Availability of more detailed spatial information of climate, soil and topography, in combination with tools with a more quantitative and mechanistic approach provides the possibility to make a deep and complex analysis similar to the real world situation, describing the maximum spatial and temporal variability in complex terrains such as the Andean Highlands. Higher levels of complexity can be reached in the analysis, including more variables within the distinct scenarios. These variables can include cultivars into each crop (i.e. native potatoes, winter wheat, short photo-period cultivars, etc.), irrigation systems, crop rotation, etc. In the same way, disaggregation of some generalizations of information, such as the ACZ, in higher spatial resolutions and for each of the different variables (Baigorria 2005), still can make more robust the spatial and temporal analysis. However, it is important to take into account the necessity of more intensive calculations to perform the process.

The possibility to analyze high-resolution maps allows different stakeholders to better make decisions, for example, from investing in N-fertilization at farmer level to decreasing taxes in N-fertilizer at political level (Crissman et al. 1998). The pixel-parcel analysis supports the strategic decision-making of a farmer, drawing the actual versus potential harvest of different crops, effectively reducing the uncertainty of the next climatic season effects on the crops. This valuable information, together with market prices, seed availability, information of plagues and diseases, and economical portfolios, as the main but not unique factors, constitute the total framework for the final decisions made by the stakeholders at different spatial and temporal levels.

11.4 Conclusions

It was demonstrated that the seasonal climate forecast of SST at global scales can be downscaled to watershed levels using empirical relations. The performance of the empirical models is affected by extreme meteorological events like ENSO; however, this gave us a clue as to how this extra information can be incorporated into the downscaling models. Uncertainties related to temporal downscaling from month to days can be partially tackled by including many realizations in the analysis, thus producing a probability distribution instead of only one value. It is of importance in carrying out an in-depth analysis of the uncertainty produced by the use of weather generators in temporal disaggregation.

The translation of the seasonal climate forecast must be performed in order to allow farmers, as well as other stakeholders at different levels, to better understand how to incorporate this information into their decision-making process. Optimal planting dates and coefficient of variation maps were well understood by farmers and governmental institutions in the area.

Acknowledgements

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Application of Seasonal Climate Forecasts for Sustainable Agricultural Production in Telangana Subdivision of Andhra Pradesh, India

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12.1 Introduction

Substantial advances in the efforts to model planetary weather systems, and resulting improvements to general circulation models (GCMs), have led to better predictability of the climate fluctuations, especially 1 to 6 months in advance (Delecluse et al. 1998). Pioneers in generation and distribution of seasonal climate forecasts include the IRI and NOAA. Wise utilization of this information by the farmers and policy makers can contribute substantially towards achieving sustainability in agricultural production. Notwithstanding constant endeavors to improve the living standards of the developing countries like India, which ranks second in the population in the world, particular challenges still remain unattended in the arena of securing sustainable food production. In this context, it is worthwhile to explore and apply climate forecasts for strategic decision-making in agriculture and related areas, especially in the semi-arid regions, which are characterized by high interannual variability in rainfall and consequent uncertainty in water availability for rainfed farming operations.

If farmers are to apply seasonal climate forecasts to improve decision-making, they must first translate forecasts into production and economic outcomes associated with alternative management strategies at the spatial scale of impacts and decisions. Locally-adapted and tested crop simulation models allow one to quickly explore the production outcomes of a range of management alternatives under a range of forecast climatic conditions (Hansen and Indeje 2004; Jones et al. 2000). However, the difference in spatial and temporal scales of dynamic seasonal climate prediction and crop simulation models presents a substantial challenge to using crop simulation to anticipate crop response to predicted climate variations. Extracting and applying information about within-season variability for crop model applications remains a more difficult challenge than downscaling in space. Several approaches for linking crop simulation models with seasonal climate forecasts have been proposed by research workers. One of the process based approaches to linking climate prediction to agricultural models is to aggregate bias-corrected climate model output into seasonal or sub-seasonal (e.g. monthly) averages, then disaggregate to produce daily time series with frequency variability that is consistent with the long-term daily record, and low-frequency variations that represent the seasonal or sub-seasonal forecasts. Temporal disaggregation involves the use of some form of stochastic weather generator approach to constrain the generated daily sequences to match predicted monthly or seasonal means or other statistical properties.

Sorghum, rice, maize and castor based cropping systems are predominant in Telangana subdivision. The total seasonal rainfall has no relevance in agricultural planning but its distribution has a major value. In the absence of advance information on the rainfall pattern, farmers plan their agricultural operations based on their experience and knowledge of the past climate. In the rainfed agricultural scenario of Telangana subdivision, dominated by the monsoon climate, the main concerns (Ramana Rao 1988) are: large variations in the dates of commencement of rainy season, variations in total seasonal rainfall received, prolonged dry spells within the rainy season, high intensity rainfall due to cyclones, depressions, etc., resulting in flood damage to the crop, and variations in the cessation date of the rainy season. Hence, early warnings based on seasonal rainfall forecasts can help farmers to adjust crop management strategies to minimize impacts of malevolent climate and maximize benefits of benevolent climate.

In addition, there is a need for multi-institutional collaboration in the region for the use of seasonal climate forecasts in analysing suitable crop management strategies, and their acceptance by the farmers and policy makers. The existing network of 107 Agrometeorological Advisory Service Units of National Centre for Medium Range Weather Forecasting (NCMRWF), which is already working towards the dissemination of farm weather advisories in Telangana subdivision, can be used towards achieving the common goal of developing crop management strategies based on seasonal climate forecasts.

This chapter addresses the application of seasonal precipitation forecasts to the management of rainfed agricultural systems in Telangana subdivision of India with the following objectives:

- a Maximize crop yield through application of seasonal climate forecast in agriculture for two selected locations,
- b Generate seasonal rainfall hindcasts for the two locations,
- c Select sowing window for selected crops,
- d Determining plant population density, and
- e Contingent planning (find alternative option when monsoon is delayed).

12.2

Methods

12.2.1

Description of Key Sites

After a detailed survey of the study area and interactions with the farmers, two contrasting sites in Telangana subdivision were selected. These sites are in two agroclimatic zones of Telangana subdivision i.e. North Telangana (assured rainfall region) agroclimatic zone and South Telangana (low rainfall region) agroclimatic zone.

12.2.1.1

North Telangana Agroclimatic Zone

North Telangana zone receives an annual rainfall of 900–1 050 mm, out of which south-west monsoon contributes 780–950 mm. The maximum temperature of the zone ranges

between 30–37 °C and minimum temperature ranges from 21–25 °C during southwest monsoon season. In this zone, Karimnagar district (longitude 79°09' E, latitude 18°26' N) was selected. This district has a population of 3.04 millions with total geographical area of 11 800 km². The source of irrigation is well and canal (Sri Ram Sagar project) with double cropped area and rice-rice and maize-groundnut based cropping system.

12.2.1.2

South Telangana Agroclimatic Zone

South Telangana agroclimatic zone receives an annual rainfall of 750–870 mm (southwest monsoon rainfall: 550–700 mm). The maximum temperature of the zone ranges between 28–34 °C and minimum temperature ranges from 22–23 °C during southwest monsoon season. In this agroclimatic zone, Mahabubnagar district was selected, which has a population of 3.51 millions with total geographical area of 18 432 km². The district is drought prone and agriculture is mainly rainfed. The major crops/cropping systems are Sorghum-Fallow and Castor-Fallow.

12.2.2

Data

12.2.2.1

Weather

The historical daily weather data were collected from the Regional Agricultural Research Station, Jagtial in Karimnagar district for 1989–2002 and Palem, in Mahabubnagar district, which are nearer to the test sites. Rajendranagar center has long-term weather data (1971–2002), which are used as proxy data for Palem. Solar radiation was calculated from bright sunshine hours. District-wise historical annual and monthly rainfall data for Karimnagar and Mahabubnagar over the past 40 years were collected for analysis.

12.2.2.2

Soil

The predominant soil type of Karimnagar district is medium to deep black soils (vertisols) with clay sub soils and red sandy soils (*Chalkas*) with 90 cm depth. The predominant soil types of Mahabubnagar district are sandy (*Dubba*) and sandy loam (red *chalka*) soils with low water holding capacity with 80 cm depth.

12.2.3

GCM Predictor Selection and Rainfall Hindcasts

Climate forecast fields for rainfall were taken from the GCMs viz. ECHAM, GSCF, CCM, COLA, NCEP with approximately 2.5–3° horizontal resolution, with 18–20 vertical levels. Output from simulations that the International Research Institute for Climate Prediction (<http://iri.columbia.edu>) provided for the present study was used.

The coarse spatial resolution of current GCMs often leads to systematic shifts in the location of spatial rainfall patterns that reduce their prediction skill. Since the large-scale features that the GCM can predict affect local climate variations, it is possible to use this information to improve prediction of local climate variability (Benestad 2001). Model correction is necessary to account for shifts in regional rainfall anomaly patterns that result from the influence of local factors that the coarse resolution of GCMs cannot capture, such as, steep orography, vegetation contrasts and land-water contrasts. The use of statistical relationships, estimated over some past period, between observed climatic predictand fields and hindcast GCM output fields, is known as model output statistics (MOS). When the predictand is at a higher spatial resolution than the GCM output, the approach is known as MOS downscaling, or statistical downscaling. One common approach to MOS correction or downscaling uses principal component analysis applied to identify the leading modes of variability of the GCM output fields, and sometimes the predictand spatial fields (Heyen et al. 1996; Kidson and Thompson 1998). The geographical domain associated with GCM output fields for principal component (PC) analysis is 66–90° E and 5–30° N. Each PC pattern represents a predictor field with high spatial resolution and spatial coherence, yet without the risk of over-fitting the empirical model. These can then be related to the predictors by regression.

In this study, IRI provided time series of PCs, using which rainfall hindcasts for selected locations were made. After the estimation of the rainfall hindcast for different months/season for the years 1989–1998 for Jagtial and 1971–1998 for Rajendranagar, the correlation was drawn between the observed and hindcast rainfall. Correlation measures the matched variances between two time series.

12.2.4

Stochastic Disaggregation of Monthly Rainfall

A stochastic weather generator that is modified to allow it to generate synthetic daily weather sequences was used such that the monthly climatic means exactly match specified targets. The underlying stochastic generator is described in Hansen and Mavromatis (2001). It is an adaptation of the WGEN weather generator of Richardson (1985). For each hindcast year we generated 10 stochastic realizations of daily weather whose monthly totals match June to September monthly totals predicted from the principal components.

12.2.5

Crop Simulation and CERES Models

Crop yields were simulated using CERES models for crops under study. The CERES (Crop Estimation through Resource and Environment Synthesis) model is a process oriented dynamic crop growth model, which predicts status of crop on real time basis as a function of exogenous parameters. The CERES models for rice, sorghum and maize crops, used in the present study are available in DSSAT v3.5 (Hoogenboom et al. 1999). It is a daily time-step model that simulates grain yield and growth components of different varieties in a given agroclimatic condition. These models have been already validated for a wide range of climates all over the world and are independent of location and soil type encountered.

Study by Saseendran et al. (1998, 2000) using CERES-Rice v3.5 showed that the model is capable predicting of grain yield and phenological development of the crop in the climatic condition of Andhra Pradesh and Kerala in India with reasonable accuracy. The errors in grain yield prediction by the model are 7.9%, 8.3% and 5.7% respectively for Sambamahsuri, Rajavadlu and Tellahamsa in Andhra Pradesh. Reddy (1992) used CERES-Maize model to predict the silking and maturity dates and yield for cv. Ganga Safed-2 in Gujarat climatic condition. CERES-Sorghum v3.5 model was also validated for cv. CSH-1 under Maharashtra climatic condition in India for its various subroutines viz. phenology, growth, water balance and nitrogen balance by Varshneya and Karande (1999), and the growth and yield were successfully predicted by model in the rainy season.

12.2.6

Management Strategies Considered

The management strategies considered for the different crops are given below. These management practices are similar to those, which are followed by the farmers at study sites.

12.2.6.1

Rice

Genetic coefficients for two cultivars, which are popularly grown in the state, are required for describing the various aspects of performance of a particular genotype in the model. The rice crop varieties used in the present study are Sambamahsuri and IR-64. The Sambamahsuri is a long duration (145 to 150 days) variety having an average simulated yield level of 6 712 kg ha⁻¹. IR-64 is a short duration (115–120 days) variety and simulated yield level is 5 623 kg ha⁻¹. The values of the genetic coefficients for the cv. Sambamahsuri (Saseendran et al. 2000) and IR-64 are presented in Table 12.1. The same crop management practices were followed in simulation experiments with different sowing dates. The planting date considered for simulation of crop cultivars IR-64 and Sambamahsuri was 26 July. Plant population at the time of planting was 33 plants m⁻² with the row spacing of 15 cm and planting depth of 5 cm. The nitrogen fertilizer was applied in three split doses of 40 kg each in the form of urea. The dates of fertilizer application were 28 July, 27 August and 1 October. The field was kept always under 2 cm of water.

12.2.6.2

Maize

Maize is generally grown as rainfed crop during rainy (*Kharif*) season in Andhra Pradesh. The maize cultivar used in the present study is ProAgro hybrid. The genetic coefficients for the cv. ProAgro was derived on the basis of cv. Ganga Safed-2, for which these values were available (Reddy 1992). The genetic coefficients along with values for cv. ProAgro were presented in Table 12.2. The farmers at the project site practiced sowing of the crop, when the accumulated rainfall is 75 mm after the onset of the monsoon. The planting window was taken from 2 June to 20 July with lowermost soil

Table 12.1. Genetic coefficients used in the CERES-Rice simulation model

Name	Description	Genetic coefficients	
		IR-64	Sambamahsuri
(P1)	Time period (expressed as growing degree days (GDD) in °C over a base temperature of 9 °C) from seedling emergence during which the rice plant is not responsive to change in photoperiod	200.0	540.0
(P20)	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate	140.0	170.0
(P2R)	Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in photoperiod above P20	350.0	400.0
(P5)	Time period in GDD (°C) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 °C	12.0	12.0
(G1)	Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis	100.0	100.0
(G2)	Single grain weight (g) under ideal growing conditions, i.e. non-limiting light, water, nutrients, and absence of pests and diseases	0.0220	0.0220
(G3)	Tillering coefficient (scalar value) relative to IR-64 cultivar under ideal conditions	1.00	1.00
(G4)	Temperature tolerance coefficient. Usually 1.0 for varieties grown in normal environments	1.00	1.00

water as 90% and uppermost soil water as 100%. Plant population at the time of emergence was maintained with 8 plants m^{-2} with the row spacing of 35 cm and planting depth of 6 cm. The nitrogen fertilizer was applied in three equal split doses of a 40 kg ha^{-1} in the form of urea i.e. at the time of sowing, 25 days after sowing (DAS), and 55 DAS.

12.2.6.3

Sorghum

Sorghum is an extensively grown rainfed crop in Andhra Pradesh, used as food, and fodder. The sorghum crop cultivar CSH-5 used in the present study is a medium duration cultivar (90–105 days), commonly grown by the farmers of Andhra Pradesh. The genetic coefficients for the cv. CSH-5 calculated by Varshneya and Karande (1999) are presented in Table 12.3. The farmers at the project site practiced sowing the crop, when the accumulated rainfall is 75 mm after the onset of the monsoon. The planting window was taken 1 June to 15 August with lowermost soil water as 70% and uppermost soil water as 100%. Plant population at the time of emergence was 18 plants m^{-2} with

Table 12.2. Genetic coefficients used in the CERES-Maize simulation model

Name	Description	Genetic coefficients for ProAgro
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod	310.0
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours)	0.520
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 °C)	900.0
G2	Maximum possible number of kernels per plant	600.0
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1})	7.90
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances	38.90

Table 12.3. Genetic coefficients used in the CERES-Sorghum simulation model

Name	Description	Genetic coefficients for CSH-5
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod	415.0
P20	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate	13.50
P2R	Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P20	40.5
P5	Thermal time (degree days above a base temperature of 8 °C) from beginning of grain filling (3–4 days after flowering) to physiological maturity	525.0
G1	Scaler for relative leaf size	10.0
G2	Scaler for partitioning of assimilates to the panicle (head)	5.5
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances	49.00

a row spacing of 45 cm and a planting depth of 5 cm. The nitrogen fertilizer was applied in the form of urea in two equal split doses of 40 kg ha⁻¹ each as basal and after 30 DAS.

12.3 Results and Discussion

12.3.1 Rainfall and Crop Yield Analysis

In order to work out the influence of rainfall variability on yield fluctuations for rice and maize in Karimnagar and sorghum in Mahabubnagar, the linear trend was fitted in the yield to remove the impact of hybrids and technological improvement. The yield deviation from the trend line was calculated for both the districts. The yield and rainfall deviations were compared and plotted in Figs. 12.1 and 12.2 for rice and maize in

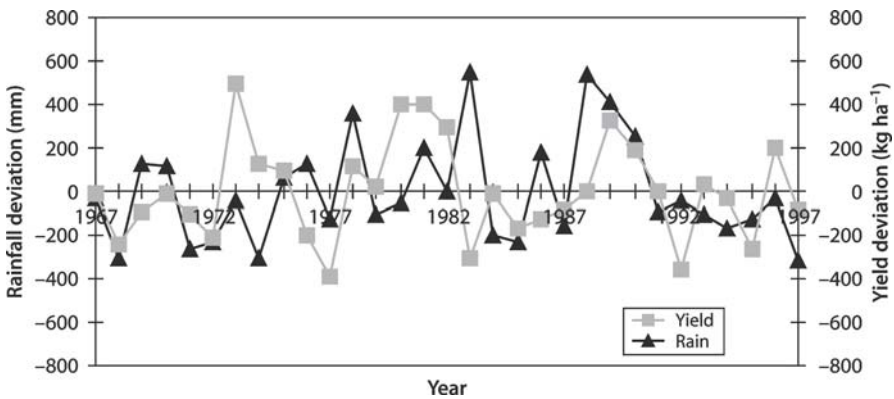


Fig. 12.1. Rainfall deviation and yield deviations for rice in Karimnagar district

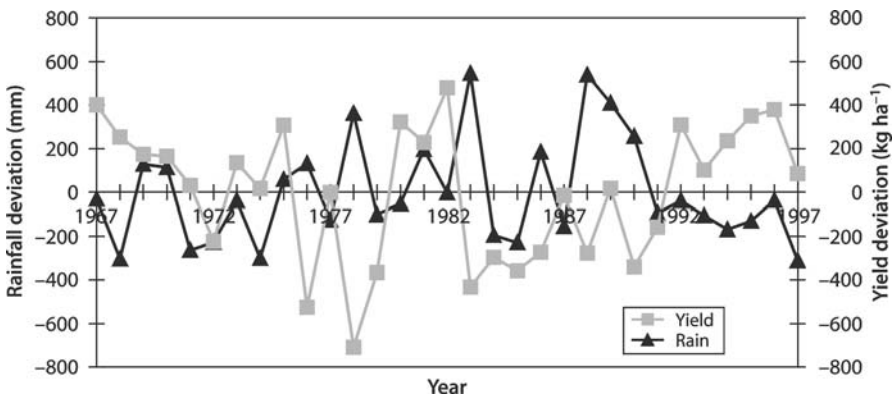


Fig. 12.2. Rainfall and yield deviations for maize in Karimnagar district

Karimnagar district respectively and in Fig. 12.3 for sorghum in Mahabubnagar district.

In Karimnagar district, the rainfall was found to have a significant influence on yield of rice and maize. In case of rice, the trend in rainfall and yield deviation was almost similar except in few years, while in case of maize, the trend was similar up to 1992 and thereafter yield increased during the period 1993–1997 (Fig. 12.2). In Mahabubnagar district, the sorghum crop showed a similar trend except during early nineties. Though maize and sorghum crops were cultivated as rainfed, the positive yield deviation during the last decade is attributed to varietal/technological advancements and even distribution of rainfall including low rainfall years.

The rainfall data of forty years (1963–2002) were analyzed to work out the variability in mean values of decadal rainfall and its coefficient of variation at different stations. Two major periods were considered (i) thirty years (1963–1992) and (ii) recent decade (1993–2002). The results presented in Fig. 12.4 show that there was a decreasing trend in rainfall in the recent decade for the months of June, July and for the whole monsoon season. The month of July is more crucial from the agriculture point of view as most of the rainfed crops are being sown and paddy transplanting is also taken-up during this month.

Coefficient of variation of mean monthly rainfall data for 1963–1982 and 1983–2002 and presented in Fig. 12.5 shows that in the Mahabubnagar district there is an increas-

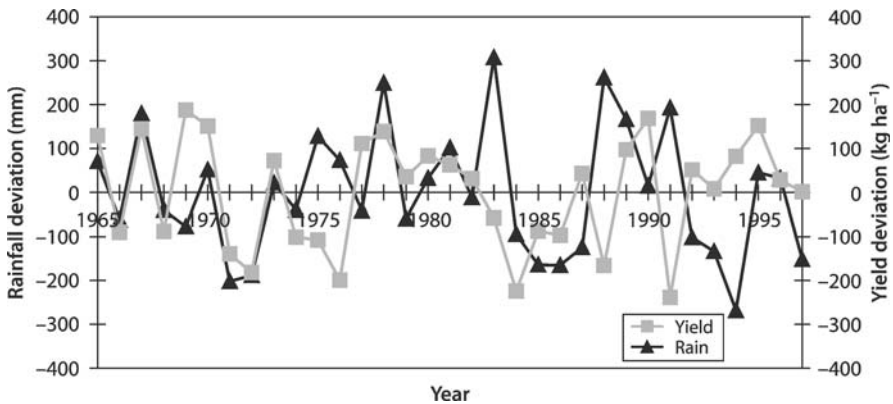
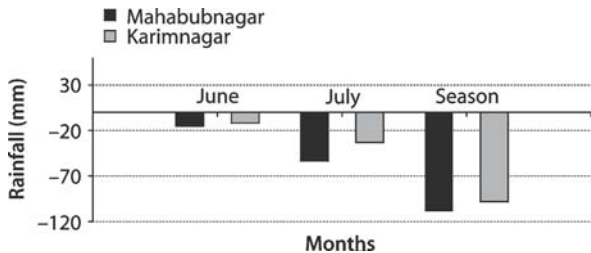


Fig. 12.3. Rainfall and yield deviations for sorghum in Mahabubnagar district

Fig. 12.4. Mean decadal (1993–2002) rainfall (mm) over three decadal mean (1963–1992) rainfall for Karimnagar district



ing trend in variability in the months of June and July and for the rainy season. Karimnagar district showed a slight decreasing trend in the month of June whereas, in July and for the rainy season there was an increasing trend.

12.3.2

Hindcast of Rainfall

Time series data on X_1 and X_2 for all five GCMs were used to estimate rainfall hindcast for the years 1989–1998 at Jagtial and 1971–1998 at Rajendranagar. Forecasts for the individual months of June, July, August, September and October and for different combinations of months were generated keeping in view the farmer's preference for a shorter duration forecasts (Table 12.4). Of all the models tested for Rajendranagar, ECHAM was found to give a better forecast (Table 12.4, Fig. 12.6). Correlation studies revealed that the

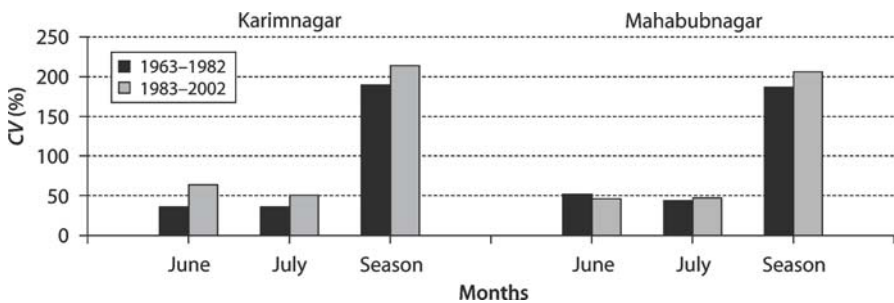


Fig. 12.5. Coefficient of variation (%) of rainfall during June, July and for the rainy season in Karimnagar and Mahabubnagar districts

Table 12.4. Correlation coefficients between observed and predicted rainfall using different climate models for Rajendranagar

	ECHAM	COLA	CCM	NCEP	GSCF
June	-0.20	-0.49	-0.30	-0.06	0.03
July	0.04	0.17	0.12	-0.02	-0.09
August	0.45	0.34	-0.20	0.13	-0.05
September	0.28	0.27	0.21	0.12	0.13
June–July	-0.36	-0.06	0.03	-0.03	-0.02
July–August	0.49	0.44	-0.07	0.13	0.00
August–September	0.59	0.47	0.15	0.24	0.16
June–July–August	0.43	0.35	-0.06	0.12	0.02
July–August–September	0.61	0.53	0.19	0.20	0.15
June–July–August–September	0.57	0.47	0.24	0.19	0.16

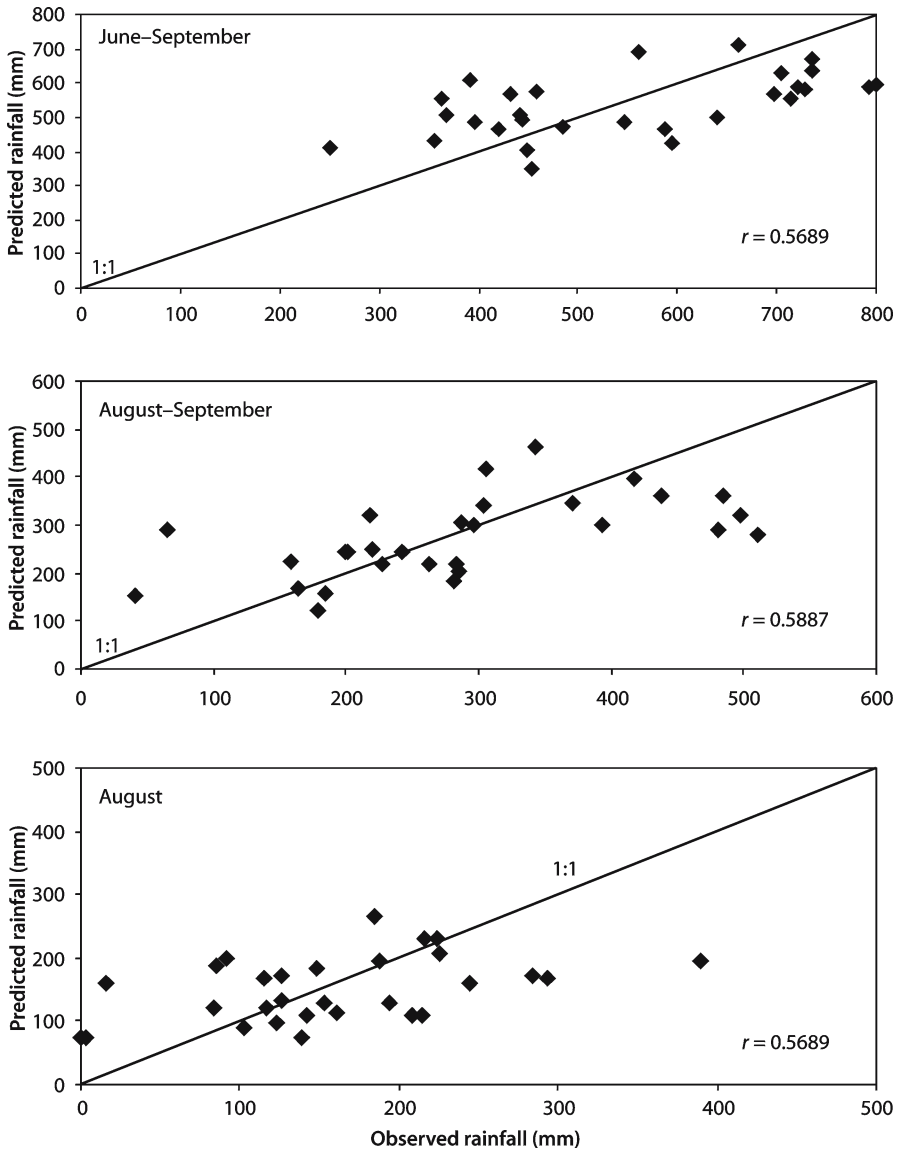


Fig. 12.6. Relationship between observed and predicted rainfall using ECHAM model for different months at Rajendranagar

highest significant correlation exists between observed and predicted rainfall when the August and September months put together were used with ECHAM model.

Similar work was also done for Jagtial (Karimnagar). At Jagtial the COLA model gave a better correlation for the season, whereas for the individual months (July, August, and September), the ECHAM model gave a better correlation (Table 12.5, Fig. 12.7).

Table 12.5. Correlation coefficients between observed and predicted rainfall using different climate models for Jagtial

	ECHAM	COLA	CCM	NCEP	GSCF
June	0.23	-0.39	-0.19	-0.32	-0.81
July	-0.38	-0.20	-0.19	0.16	-0.15
August	-0.12	-0.09	-0.32	-0.16	-0.24
September	0.23	0.01	-0.30	-0.20	-0.17
June–July	0.00	0.15	0.03	0.08	-0.42
July–August	-0.16	0.18	0.04	0.12	0.13
August–September	0.02	0.25	-0.25	-0.06	-0.36
June–July–August	0.13	0.28	0.00	0.09	-0.28
July–August–September	0.20	0.35	0.13	0.21	0.01
June–July–August–September	0.24	0.44	0.09	0.17	-0.31

12.3.3

Crop Yield Simulation with Actual and Hindcast Rainfall

12.3.3.1

Optimum Transplanting Time for Rice

Simulation results of grain yield of rice cv. IR-64 and Sambaamahsuri for 12 different dates of transplanting revealed that the rice yield is higher for cv. IR-64, when transplanted on 26 July as compared to other transplanting dates and for cv. Sambamahsuri, higher yield was obtained when transplanted on 19 July.

12.3.3.2

Crop Model Output with Hindcast Weather

Rice

The ten realizations of weather data conditioned on sub-seasonal (monthly) rainfall hindcasts made from each GCMs were generated and crop yield was simulated with generated weather for each realization with the same management practices as with the observed weather data for cv. IR-64 and Sambamahsuri. Further average of yield from 10 realizations for each year was worked out. Comparisons of yield based on hindcast and observed weather are shown in Figs. 12.8 and 12.9.

Maize

Comparison of the grain yield of maize simulated by the model with the hindcast and observed weather data for cv. ProAgro. Figure 12.10 shows that grain yield simulated with NCEP generated weather has the same trend as that of observed weather.

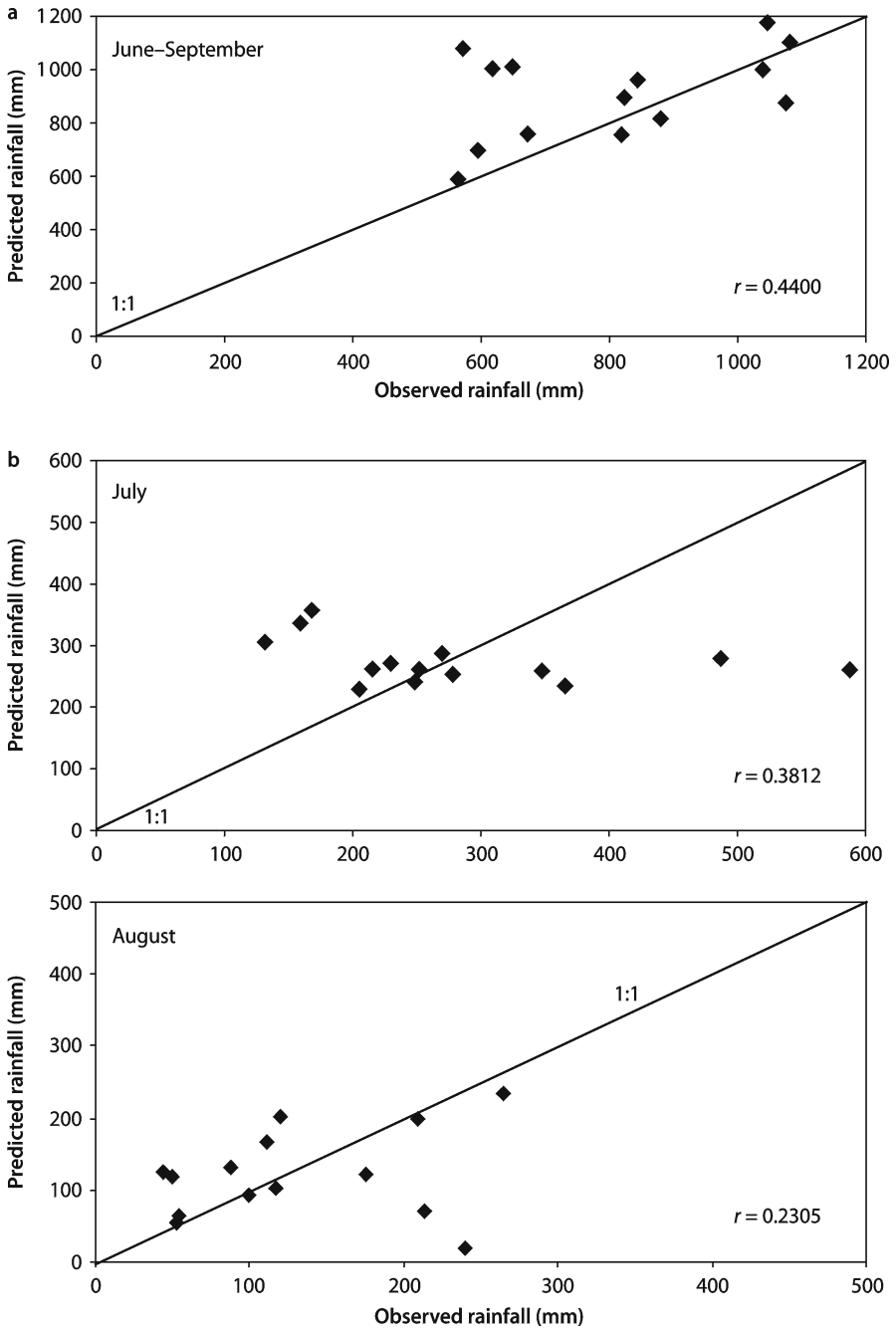


Fig. 12.7. Relationship between observed and predicted rainfall for Jagtial using; a COLA model; b ECHAM model for different months

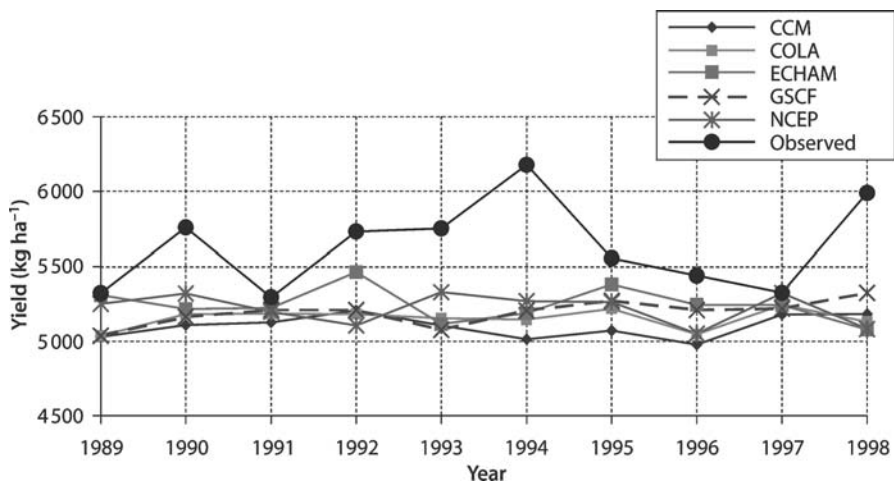


Fig. 12.8. Comparison of simulated rice yield (cv. IR-64) with observed and hindcast weather data

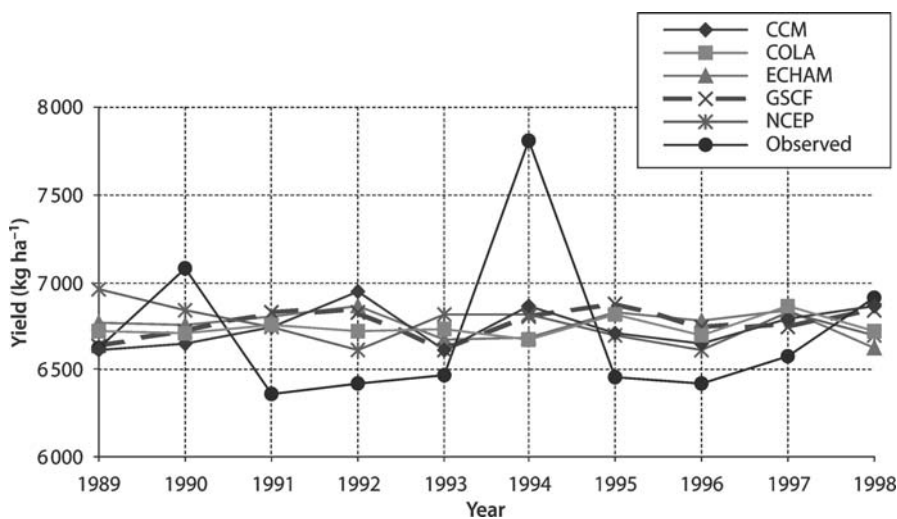


Fig. 12.9. Comparison of simulated rice yield (cv. Sambamahsuri rice) with observed and hindcast weather data

Sorghum

The grain yield comparisons for the sorghum crop (Fig. 12.11) indicate that ECHAM model predictions were closer to the observed yield data in few years and also within the same trend.

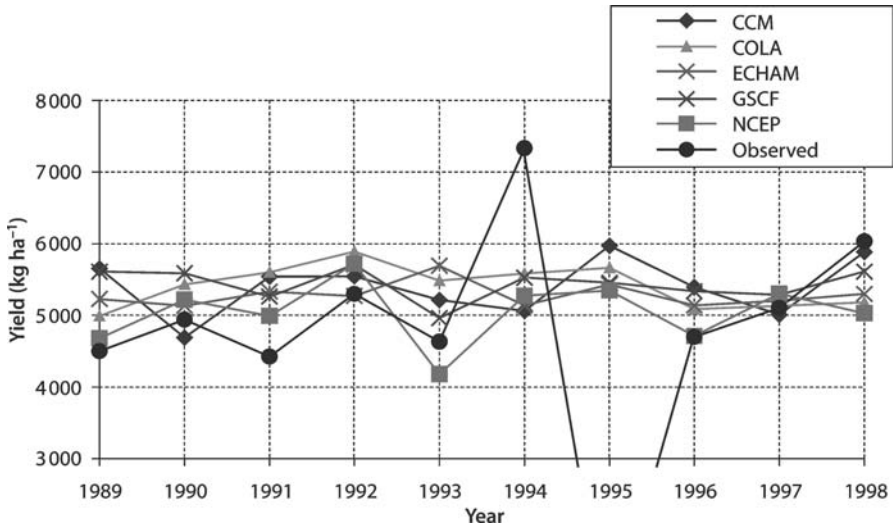


Fig. 12.10. Comparison of simulated maize yield (cv. ProAgro maize) with observed and hindcast weather data

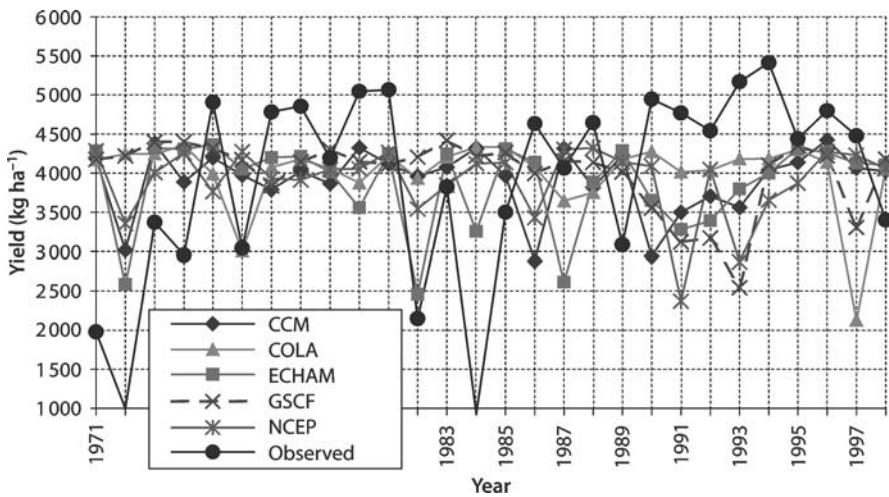


Fig. 12.11. Comparison of simulated sorghum yield (cv. CSH-5) with observed and hindcast weather data

12.3.4 Farmers Perceptions

Awareness programs were conducted periodically during monsoon season of year 2003 on seasonal climate forecasts for the farmers of both the key sites. The main aim of

this exercise was to elicit farmers' views on the use of climate forecasts in their cropping strategies and the farmer's requirements. Farmers mentioned about the weekly medium range forecasts based AAS activities and long range forecasts (LRF) of India Meteorological Department given in the beginning of monsoon season. They expressed that they are unable to make use of LRF in their crop planning. Farmers were informed about the efforts being made to generate seasonal climate forecasts (SCF) for Indian region by leading international centers viz. IRI and their limitations. Interactions with the farmers brought out their following needs about weather and climate forecast:

- Start of rainy season (i.e. monsoon onset)
- End of rainy season
- Break in monsoon
- Extreme weather events
- Preferred monthly/fortnightly forecast

During the subsequent meetings, the farmers were educated on the use of SCFs and their limitations. In short-term planning of agriculture operations the importance of medium range forecasts was explained during these interactions. The farmers expressed satisfaction to a certain extent on the use of agro-advisory services based on medium range weather forecasts. The farmers suggested to increase the lead-time with 10–15 days. Further they felt the need to integrate the seasonal/long range climate forecasts with agro-advisory services. They suggested that this integration will help to select the right crop and the right variety based on seasonal climate forecasts and mid-season corrections like intercultural operations, supplemental irrigation, etc. using medium range forecasts.

The views of the farmers from two agroclimatic zones were also taken during extensive tours. The requirements differ between the zones. Low rainfall zone farmers are interested in correct forecast of sowing rains that is very critical. High rainfall zone farmers are interested in knowing the quantum of rainfall required to get the tanks filled up and subsequent release for paddy transplantation.

12.4

Conclusions

Results of this study showed that ECHAM model has generated a better rainfall hindcast at seasonal/sub-seasonal scale for Rajendranagar (a proxy station for Palem). For Jgatial COLA model gives better correlation between hindcast and observed rainfall at seasonal scale whereas for individual months ECHAM produced better hindcasts. Awareness was created amongst the farmers, researchers and planners about utility and limitations of seasonal climate forecast for application in agriculture through group meeting during monsoon season 2003 was created. Farmers preferred fortnightly and monthly instead of seasonal forecasts for better decision-making in agricultural operations and desired for integration of ERP along with existing AAS.

Acknowledgements

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Localized Climate Forecasting System: Seasonal Climate and Weather Prediction for Farm-Level Decision-Making

R. Rengalakshmi

13.1

Introduction

Recent developments in weather and seasonal rainfall prediction have increased the accuracy and reliability of forecasts of the Indian monsoon. Despite these advances, availability and access to location-specific forecasts to take proper decisions at the farm level is very limited. Traditionally farmers in India have been using a set of indicators that have varied levels of dependability for rainfall prediction and have evolved several coping strategies and mechanisms.

The M. S. Swaminathan Research Foundation (MSSRF), based at Chennai, India initiated a project on “*Establishing decentralized climate forecasting system at the village level*” to create and enhance farmer’s capacity to use locale-specific seasonal rainfall and weather forecasting in collaboration with Reddiyarchatram Seed Growers Association (RSGA), a farmers association at Kannivadi in Dindigul district of Tamil Nadu state, India. The main goal of the project is to create an access and enhance farmers’ capacity to use location specific seasonal climate and weather predictions to improve their livelihoods. The major objectives are to study the seasonal climate variations and chronicle the farmer’s traditional coping strategies and knowledge. The study also aims at evolving a methodology for downscaling with appropriate institutional linkages and converting the generic data into location-specific, medium term, inter- and intra-seasonal climate and weather forecasts. Probabilistic seasonal climate and weather forecast information is translated into appropriate farmer friendly versions for its practical use in crop management.

13.2

Study Area

Reddiyarchatram block is a semi-arid region located in Dindigul district of Tamil Nadu, India, covering a geographical area of 280 km². More than 80% of the households in the district depend on agriculture. Important planting seasons are June–July and October–November for both the irrigated and rainfed crops, in addition to the summer irrigated crop. The mean annual rainfall is 845.6 mm. Rainfall in the region is characterized by a large variation between seasons. Though the area benefits both from the northeast monsoon (October–December) and the southwest monsoon (June–September), maximum percentage (52.5%) of rainfall is received during the northeast monsoon and nearly 25.8% of the total annual rainfall is received during the southwest monsoon. The area receives only 5.4% of the total annual rainfall during January and February and nearly 16.3% during the summer seasons between March and May. The

total area under cultivation is 24 624 ha which includes both dry and irrigated lands. Approximately 29 600 households are involved in agriculture and more than 50% of the households are small and marginal farmers. Sorghum, small millets, grain legumes, cotton and chickpea are the major annual crops cultivated under rainfed conditions. Cotton, maize, flower crops, vegetables, gherkins, sugarcane, annual moringa, paddy, onion, etc. are the most important annual crops grown in this region. The major source of irrigation is underground water through wells followed by small tanks and reservoirs.

13.3 Methodology

The study was initiated during October 2002 to March 2004 in five villages where Village Knowledge Centers (VKCs) are functioning. The computer based Village Knowledge Centers with Internet connection provides static information about the agronomical practices of the different crops cultivated in the region and the dynamic information like price details of the main agricultural produce from different markets, availability of inputs, farmers entitlements, etc. A set of VKCs are operating in the region connected with a 'hub' in the center and the 'hub' is the nodal point, which receives the generic information and adds value by converting it to local specific information. The local community manages the VKCs; access is ensured to all irrespective of caste, class, gender and age. Need based content creation is being regularly done on the basis of the feed back from the local women and men farmers. The local village people have been trained in the management of modern information and communication technologies including networking.

In each village, traditional knowledge system on weather and climate forecast was studied through conventional survey using questionnaire, anthropological tools such as participant observation, and participatory developmental tools such as Venn diagram and Focus Group Discussions (FGD). The traditional weather and seasonal rainfall predictors were studied among the selected sample households through questionnaires. Anthropological tools such as open-ended interviews were used to study the metaphors, folklore and proverbs that gave a better perspective on the traditional knowledge. A series of Participatory Rural Appraisals (PRAs) were organized in representative villages in the block that focused on the social system, existing natural resources, agricultural seasons and rainfall patterns and also on the prevailing pattern and system of information flow. The needs, constraints and coping strategies on weather and climate of farmers and agricultural laborers were assessed through FGD and these views were triangulated through informal discussion with knowledgeable men and women farmers.

MSSRF facilitated linkages to get the scientific forecast between hub of the VKCs and National Centre for Medium Range Weather Forecast (NCMRWF) for medium range weather forecast and the Tamil Nadu Agricultural University (TNAU) for seasonal rainfall forecast. The hub center manages a 'B' observatory; animators were trained in observatory management with the technical support of TNAU. They regularly record the local weather parameters (maximum and minimum temperature, soil temperature at different depths, sunshine hours, wind direction and velocity, evaporation rate, relative humidity) according to the norms of Indian Meteorological Department in the prescribed format and communicate the same to NCMRWF twice a

week through electronic mail. In turn NCMRWF provide weather forecast twice a week to the hub center on cloud cover, precipitation, temperature, wind direction and wind velocity. Similarly, linkages were established to receive the seasonal rainfall forecast from TNAU.

The hub center receives the forecast and converts the generic information received from these two institutions into location-specific farmer friendly language (for example if the wind direction is 100° , it is communicated to the particular village in their local parlance) and disseminates the information to farmers and agricultural laborers through VKC, bulletin boards and local newspaper to the farmers.

Initially MSSRF trained the animators to convert the generic information into farmer friendly versions. The information is being communicated to other VKCs through fax mode and can be accessible through multimedia folders using Internet. The messages are communicated to nearby villages by the VKCs through bulletin boards that are located in 15 different villages. A Focus Group Discussion was carried out in each of the villages with the men and women to communicate the forecast. Initially we explained the method by which the scientific forecasts were generated and its attributes to the farmers. The probabilistic nature of the seasonal rain forecast was explained to the farmers, and simple locally familiar games were organized to clearly explain the concept of probability. Then using the climatological data analysis 'probability of exceedance' graph was generated to explain the relationship between rainfall amount (forecast) and probability. Attempts are being made only to communicate the forecast information to the people instead of giving follow-up advisories. It allows the farmer to take their own decisions, because under the varied cropping pattern and rainfed situations, farmers take decisions based on the event of rainfall and follow dynamic strategies instead of a single strategy as most of the forecasters recommend. The entire process is institutionalized through these VKCs.

13.4

Results and Discussion

Understanding people's perceptions and knowledge of weather and climate is critical for effective communication of scientific forecasts. The knowledge is learned and identified by farmers within a cultural context and the knowledge base follows a specific language, belief and process. The local men and women members assess, predict and interpret by locally observed variables and experiences using combinations of plants, animals, insects, and meteorological and astronomical indicators. Farmers use different kinds of traditional knowledge for rainfall prediction based on their observation with different types of phenomena like wind movement, lightening, animal behaviors, birds movement, halos/rings around the moon and the shape and position of the moon on 3rd to 5th day from the formation, etc. This type of knowledge provides a framework to explain the relationships between particular events in the climate and farming. Farmers use different types of predictors (based on environmental and biological criteria) in combination to take critical farming decisions and to decide on adaptive measures. The knowledge is evolved by locally defined conditions and needs, in other words this knowledge is context specific.

Men and women have different kinds of knowledge and use it for different purposes. Similarly village elders are more knowledgeable and are able to use more indi-

cators with greater understanding of the reliability of various indicators. The older men and women were able to provide more than 12 indicators with different lead times, whereas the middle aged (25 to 35 years) persons could provide only 3–4 indicators. Farmers as well as agricultural laborers have their own indicators that are based on their need and interaction. Also, farmers are able to provide more indicators than the agricultural laborers. The variations in the indigenous knowledge in a community are based on age, gender, caste, class and literacy.

The indicators clearly show that this indigenous knowledge on seasonal rainfall and weather is qualitative in nature. Weather predictions are used to take short-term decisions both in the irrigated and rainfed systems. It helps the small and marginal farmers to plan various agronomic practices more effectively especially at the time of sowing, weeding, spraying of chemicals and harvesting and post harvest operations. However, farmers use seasonal rainfall predictions to prepare themselves for anomalies related to rainfall. For example it helps to decide the cropping pattern for that season, if the rainfall is normal, they can go for high value crops like maize with high yielding varieties, otherwise if it is below normal they can plan for short duration drought resistant pulses and small millets. Farmers have been using different strategies to adapt and cope up with uncertain weather and climate based on their experience and acquired knowledge from previous generation. The important decisions are selection of cropping system, mobilizing seed, fertilizer and application, decisions on sowing (early or late), land and bed preparations, mid season corrections such as reducing population/providing irrigation. Similar to the seasonal forecast, weather forecast is being useful for the small and marginal farmers to plan the agronomic practices more effectively especially at the time of sowing, weeding, spraying of chemicals and harvesting and post harvest operations.

In the Focus Group Discussion farmers expressed that the increasing variability in rainfall have reduced the farmers' confidence in their own predictors and hence they are increasingly looking for scientific forecasts. They expressed the variability in terms of more water deficit years, late onset of rains and premature end of rains, and irregular distribution in time and space. Climatological analysis of the inter annual variability using 20 years of annual rainfall in this region indicated that the variability was about 36% and across the seasons the variability in terms of CV is high during the southwest monsoon season (71.6%) followed by the northeast monsoon season (52.2%). Hence, the challenge and necessity is to provide reliable forecasts through appropriate methods based on the needs of the farmers.

During 2003 and 2004 winters, monsoon rainfall amount was predicted and communicated to the farmers. Based on the two years experience, farmers indicated that it is very difficult to take decisions in the farm based on this forecast information. Instead, it might help them to prepare against anomalies in the future, provided the forecasts are accurate over years. Though farmers are listening and carefully monitoring the correlations, they expressed that they need time to observe the effectiveness of scientific forecasts over seasons or years. Based on the request of the farmers, four rainfall measuring devices were installed in different villages in this region and the rainfall was carefully recorded by the Knowledge centers.

Farmers expressed that their traditional practice follows dynamic strategies based on the event of rainfall, which is completely different from following a single strategy

based on one prediction before the crop cultivation. They expressed that their existing strategies are more practical, evolved locally over years through trial and error considering the available natural resources. Thus the forecasts of a single rainfall amount do not support taking any short-term (e.g. like crop variety or plant population per unit area) or long-term decisions (like cropping system: monocropping or mixed cropping, etc.). Another important issue is that the probabilistic mode of the total amount of rainfall does not support farmers' need in terms of time of onset of rainfall and its distribution. It is one of the significant variables requested by the farmers to make decisions on initial agricultural activities, which may help to reduce the risk. Though farmers could understand the probabilistic nature of the rainfall over season, they expressed that it is very difficult to operationalize it, since it is not providing confidence (moral support) to the farmers, instead it indicates the lack of certainty and based on this they could not take major decisions. Also the two years experience indicates that learning takes time (observation over time/seasons) and the use has to do with familiarity.

With regard to the medium range weather forecasts, attempts are being made only to communicate the forecast to the people instead of giving follow-up advisories based on the forecasts. It allows the farmer to take decisions based on his/her field conditions. This is because under local situations, due to the heterogeneous nature of the field and crop conditions farmers take decisions based on the event and they have been following dynamic strategies instead of a single strategy which the forecasters recommend. A survey was organized to know the impact of the forecast information and nearly 66% of the farmers expressed that they have used it for taking farm management decisions. Around 72% of the farmers expressed the need for receiving forecasts at a much longer lead time interval, mostly 10 to 15 days.

13.5 Preliminary Conclusions

The study clearly brought out the importance of the vast traditional knowledge of the farmers on rainfall prediction and their understanding of its reliability through their observation, experience and practice in the field. The social stratification influences the evolution and management of knowledge. Understanding the local people's perceptions on rainfall prediction is necessary to communicate the scientific forecasts, since it is learned and identified by farmers within a cultural context and the knowledge base follows the specific language, belief and process. Intensive participatory dialogue between the scientific knowledge providers and user group's helps to define the strategies for using the forecasts in combination with traditional knowledge and skills. The project helped us to understand that, to develop a decentralized forecasting system at the village level needs a participatory approach to mobilize the farmers around the technology. On the other hand, access, availability of infrastructure, skill and expertise are crucial to develop reliable region-specific scientific forecasts to serve the farming societies. Farmers may not heavily rely on scientific forecasts until the forecasts have proven its reliability. At this phase due to the limited experience and observation it is difficult to derive any conclusion. It helps us to set the system and in the process slowly build up the farmers' understanding and confidence in scientific forecasts.

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Use of Sea Surface Temperature for Predicting Optimum Planting Window for Potato at Pengalengan, West Java, Indonesia

R. Boer · I. Wahab

14.1 Introduction

Pengalengan is the main potato production center in the Bandung district of Indonesia. About 76% of potato production of this district comes from Pengalengan, while contribution of Bandung to total production of West Java was about 60%. A significant reduction in the production in this subdistrict will have a great influence on potato supply in the region. Farmers at Pengalengan plant potato almost throughout the year. They divided the planting season into three seasons, i.e. Porekat (January–April), Ceboran (May–July) and Wuku (September–December). The area planted to potato in Ceboran is much lower than in other two seasons as it is the dry season and farmers normally use paddy fields or lands close to water sources or irrigation facilities. Farmers plant their dry lands with potato only in the Wuku and Porekat seasons. Thus planting dry lands commences after the onset of wet season (normally early September).

Many studies indicated that ENSO affects rainfall characteristics in various forms (Soerjadi 1984; USDA 1984; ADPC 2000; Yoshino et al. 2000; Kirono and Partridge 2002). First, during El Niño years, end of the dry season occurs later than normal, while during La Niña years it occurs earlier. Second, the onset of the wet season is later than normal during El Niño and advanced during La Niña years. Third, during El Niño years a significant reduction of dry season rainfall could be expected and a significant increase during La Niña years. Fourth, long dry spells occur during the monsoon period, particularly in eastern Indonesia.

At Pengalengan, during the El Niño years false rains sometimes occur in early September and this normally prompts farmers to start planting. Farmers who start planting early September while the onset of rainy season delayed to October or November would have crop failure or get low yields due to poor emergence. On the other hand, farmers who delay their planting up to November due late onset of rainy season may also have low yields as the seeds they used would have lost their viability. According to farmers, seeds still have good viability if they are stored not more than three months. Thus farmers who used the seeds produced in Porekat season for the late Wuku season may not get good yields. These results suggest that farmers used the information on the onset of rainy season at least for two purposes (Boer et al. 2004). First is to determine the suitable planting time for Wuku season. Second is to define the suitable time for planting at Ceboran season for seed production used in the coming Wuku season. Therefore a method for predicting optimum planting window based on ENSO forecasts needs to be developed. This chapter describes the methodology for deter-

mining optimum planting windows for potato planted in dryland using sea surface temperature information prior to the planting season.

14.2 Methodology

Determination of optimum planting windows for potato planted in the drylands at Pengalengan follows a number of steps. The first step is to evaluate the strength of relationship between sea surface temperatures and rainfall variability at Pengalengan. The second is to collect potato yield data throughout the season for validating the crop simulation model (DSSAT). The third is to simulate potato yield data using historical climatic data under different planting times throughout the year. The fourth is to carry out curve fitting for yield data against planting date for each year of simulation. The fifth is to determine the planting time that gives maximum yield from the fitted curve for each year of simulation (called optimum planting time). The sixth is to determine optimum planting windows from the distribution of optimum planting times. The seventh is to develop equation for determining optimum planting time from sea surface temperature prior to planting season.

The strength of the relationship between sea surface temperatures and rainfall variability at Pengalengan was assessed using CLIMLAB (Tanco and Berri 1999) based on monthly rainfall data for 11 stations with length of record of more than 20 years. This analysis was done to ensure that rainfall variability at Pengalengan was significantly affected by sea surface temperature phenomena that occur in the Pacific and Indian oceans. *SOI* (Southern Oscillation Index) and *DMI* (Indian Dipole Mode Index) were used to represent conditions that occur in the Pacific and Indian Ocean respectively. Indian Dipole Mode is similar to El Niño where a warm pool in the Indian Ocean moves eastward in a cycle of 3 to 7 years (Saji et al. 1999). Indian Dipole Mode Index is defined as the difference in SST anomaly between the tropical western Indian Ocean (50–70° E, 10° S–10° N) and the tropical southeastern Indian Ocean (90–110° E, 10° S–equator).

Data on potato yield were collected from 28 farmers that planted their crops in the period between June 2002 and February 2003. Planting time and crop management practices used by the sample farmers were recorded. Physical and chemical properties of soils were also analyzed. These data were used as inputs for the crop simulation model and the observed yield data were then used to validate the crop simulation model. The DSSAT potato model was run using 20 years observed daily rainfall data (1982–2001) under no irrigation at different planting times (started from 1 January with 15 days interval) with 10 management practices which were defined based on the technology practices used by farmers. Furthermore, Fourier regression was used to develop curves to fit seasonal pattern of the potato yield. The equation so fitted is as follows:

$$Y_t = a_0 + \sum_{k=1}^n (b_k \sin(kt') + c_k (\cos(kt'))) \quad (14.1)$$

where a_0 , b_k and c_k are regression coefficients, $k = 1, 2, \dots, n$ is harmonic number, $t' = 2\pi t / 365$, $t = 1, 2, \dots, 365$ is Julian day and Y_t is yield of potato at planting time of t .

The coefficient a_0 represents the annual mean of yield. The maximum yield can be estimated from $a_0 +$ maximum value of C_t , where

$$C_t = \sum_{k=1}^n (b_k \sin(kt') + c_k (\cos(kt'))) \quad (14.2)$$

The number of Fourier regressions developed was 200 equations (20 years of climatic data \times 10 management practices). The distribution of optimum planting times was developed and used to define the optimum planting window. Finally, the equation to estimate optimum planting time from *SOI* and *DMI* prior to planting season was developed. This equation could then be used to predict optimum planting windows under different *SOI* and *DMI* condition.

14.3

Results and Discussion

The results of analysis suggested that rainfall variability at Pengalengan is strongly affected by global phenomena occurring in the Pacific (represented by *SOI*) and Indian Oceans (represented by *DMI*). May to August rainfall (called as Ceboran season) for most of the stations was significantly related with sea surface temperature in the Pacific Ocean, while September to December seasonal rainfall (called Wuku season) for some of stations was also significantly related with sea surface temperature in the Pacific Ocean and also with Indian Ocean. Further analysis showed that the July–October anomaly rainfall (AR_{J-O}) of all stations was significantly correlated with May–June *SOI* and *DMI*. The form of relationship can be written in the following equation:

$$AR_{J-O} = a + b(SOI_{M-J}) + c(SOI \cdot DMI)_{M-J} \quad (14.3)$$

The R^2 of the equations ranged between 22 and 56% with mean of about 37% and the values of coefficients b and c are all equal or more than 0 (Boer and Faqih 2004). This means that if the *SOI* is negative (indicating El Niño) and *DMI* is also negative (sea surface temperature in the region of 90–110° E/10° S–equator, near Indonesia is higher than that of 50–70° E/10° S–10° N), the ($SOI \times DMI$) value will be positive. This means that a negative *DMI* will counteract the reducing effect of El Niño on rainfall. This finding is in agreement with previous studies (Yamagata et al. 2001; Kumar et al. 1999).

The crop simulation model was also able to mimic the real system. The simulated yields followed the observed yields well (Fig. 14.1a). The correlation between the observed and the simulated yield was about 0.86 (Fig. 14.1b). This suggests that the simulation model is able to capture the impact of crop management and climate variability on potato yield. Based on means of 200 simulated yields (20 years of climatic data \times 10 management practices), it was found that under no irrigation, the crop would produce higher yield if it were planted in Wuku season (Fig. 14.2). Furthermore from the 200 fitting curves (Eqs. 14.1 and 14.2) the planting dates which give maximum yields were defined and distribution of the optimum planting was then developed as shown by Fig. 14.3a. It is clearly shown that the optimum planting window for potato at

Fig. 14.1. a Comparison between observed and simulated yield; b relationship between observed and simulated yield from DSSAT

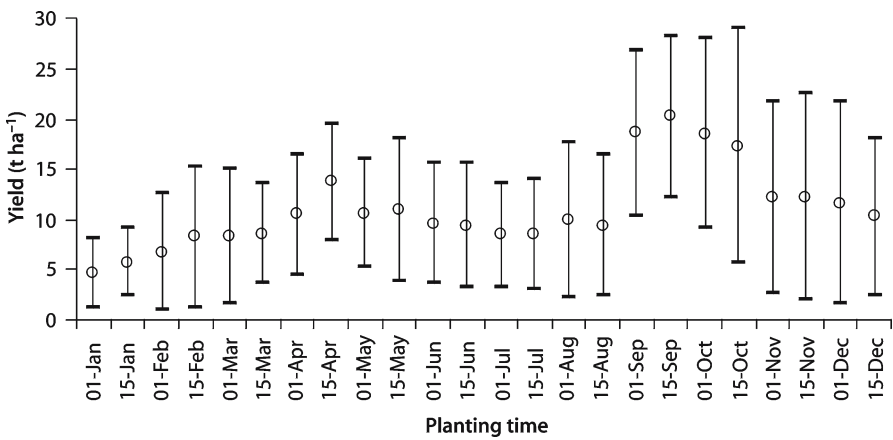
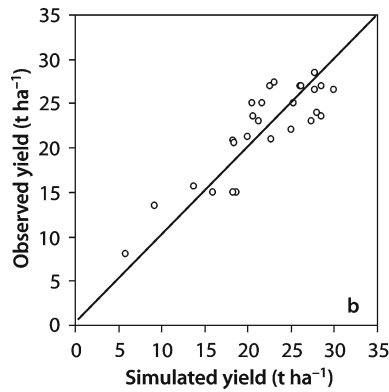
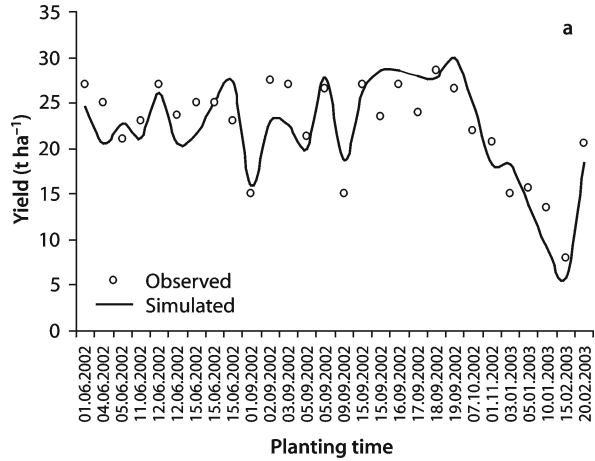
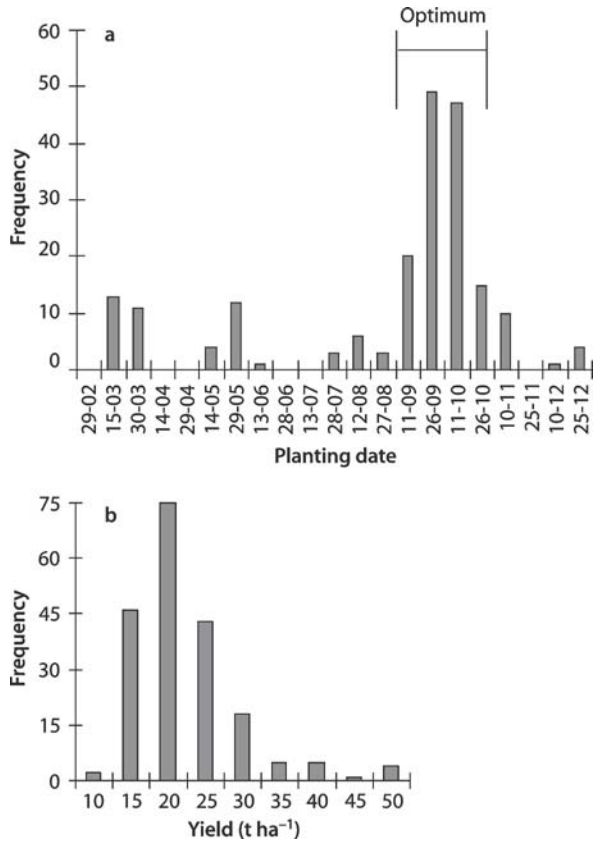


Fig. 14.2 Mean yields of potato crops from the 10 management practices across 20 years of simulation (1982–2001)

Fig. 14.3. a Distribution of optimum planting time; b potato



Pengalengan is between 11 September and 10 November and the maximum yields are mostly more than 20 t ha⁻¹ (Fig. 14.3b). The minimum yields where farmers will have the break event point was 10 t ha⁻¹ (price of potato per kilogram was about Rp 2 000 and production cost was Rp 20 000 000 ha⁻¹).

As *SOI* and *DMI* have a significant impacts on rainfall variability, and rainfall variability has a significant impact on yields variability, the *SOI* and *DMI* can be used to define optimum planting time (*OPT*). The results of this analysis suggested that the optimum planting time for Wuku could be predicted from mean July–August *SOI* and *DMI*. The form of the equation is the same as the equation that related July–October anomaly rainfall with *SOI/DMI*, i.e.:

$$OPT_W = 272 + 0.843(SOI_{JA}) - 1.57(SOI \cdot DMI)_{JA}; R^2 = 19\% \tag{14.4}$$

This suggests that when El Niño occurs (*SOI* negative) but *DMI* is also strongly negative, the onset of rainy season may not be delayed and therefore planting early in the Wuku season should have no risk. But if the *DMI* is strongly positive, then planting early in the Wuku season (early September) is not suggested (Fig. 14.4). This ap-

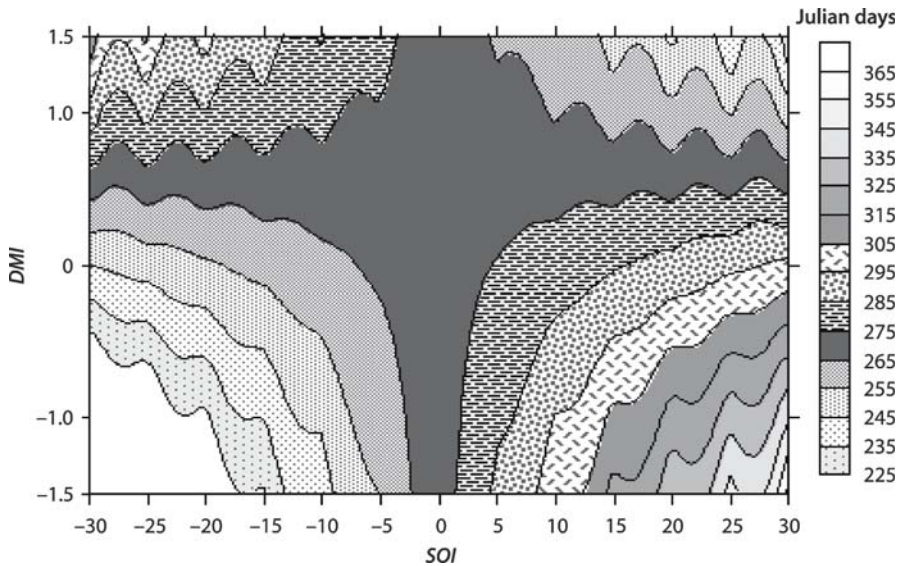


Fig. 14.4. Recommended planting time for Wuku season based on July–August SOI and DMI

proach can also be used to estimate the expected yield of potato planted in Wuku season from July–August SOI and DMI as demonstrated by Boer et al. (2004).

Acknowledgements

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Climate Forecast for Better Water Management in Agriculture: A Case Study for Southern India

R. Selvaraju · H. Meinke · J. Hansen

15.1

Introduction

Groundwater, the most assured widely available source of irrigation water, influences India's industrial and agricultural growth (Rao et al. 1996). About 12.5% of India's annual precipitation percolates into the groundwater, where it is protected from evapotranspiration. Demand for water by the agricultural, domestic and industrial sectors has increased considerably over the years, resulting in unsustainable exploitation of groundwater resources. The number of wells has increased from 7.78 to 9.98 million (dug out), 2.13 to 4.77 million (shallow tube) and 33.3 to 49.1 million (deep tube) over the last 10 years. Continuous cropping reduces potential recharge by reducing downward flux of rainfall (O'Connell et al. 1995). Although vast, India's groundwater resources are not inexhaustible, as evidenced by continuous decline in groundwater levels in regions such as the Coimbatore district in western Tamil Nadu.

Efforts to ensure effective use and augmentation of water resources have not produced the intended results. Frequently farmers are forced to abandon crops mid-season due to lack of water, resulting in economic hardship. Management techniques that account for climatic variability and optimize the use of scarce groundwater resources would help to alleviate such hardship. The aim of the study is to assess the impact of ENSO-related climate variability on rainfall, groundwater resources and irrigation requirements, and to explore the impact that using such knowledge might have on irrigated crop production systems in the semi-arid western agroclimatic zone of Tamil Nadu.

15.2

Description of the Study Area

For this study we selected the Coimbatore district (10°12' to 11°24' N, 76°39' to 77°30' E) of Tamil Nadu State in southern India. Of the district's 746 800 hectares, 43% is cultivated. The region's climate is classified as hot semi-arid. The dominant soils are red (alfisols) and black (vertisols). Lack of irrigation water results in 20% of arable land left fallow in any year. The major irrigated crops in this region are maize, rice, pulses, sugarcane, turmeric and banana (Fig. 15.1). Banana, sugarcane and turmeric are the long duration (–10 months to one year) crops in this region. Vegetables are also grown and sold in daily markets to provide cash flow. Recently maize gained additional importance as poultry feed, which is also sold in local markets. Both maize and vegetables are grown during summer monsoon (June–September) season as well as from December to May if sufficient irrigation water is available.

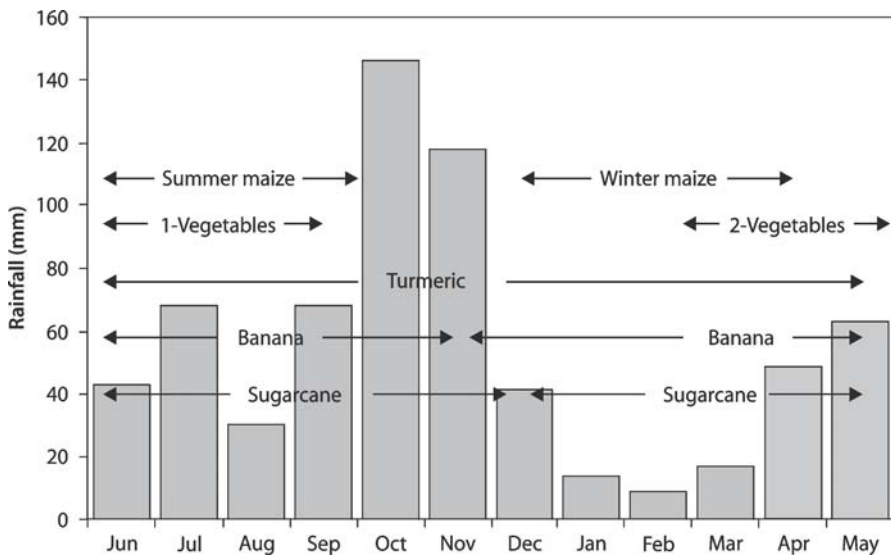


Fig. 15.1. Schematic of the irrigated crop production systems in Cimbatore district, Tamil Nadu, India

Groundwater from 94 271 open wells is the dominant source of irrigation. Bore wells are often dug to depths of more than 200 meters. The district has 77 small to medium tanks, most of which are poorly maintained. Significant groundwater recharge occurs during winter monsoon (October–December), which contributes 47% of the total annual rainfall. Farm-level storage structures like check dams, tanks and percolation ponds fill during the wet season providing sufficient opportunity time for infiltration and recharge. On average the summer monsoon (June–September) contributes only 33% to the total annual rainfall, and thus recharge during the season is relatively low.

15.3 Farm and Farmers Characteristics

In two villages (Malayapallayam and Kanur pudur) we conducted detailed surveys of farmers ($n = 60$) to elucidate their specific information needs, ascertain their degree of vulnerability and document prevailing socio-economic conditions. For this we used semi-structured questionnaires and participative methods such as focus group interviews. We also conducted an independent survey with 37 farmers in Kootapalli village to assess the impact of climate variability on income inequality at the farm household level. For a quantitative assessment of income inequality we used the Gini coefficient (G).

$$G = \frac{2}{n\mu} \text{cov}(y,r)$$

where n is the number of observations, y refers to the series of total incomes, and r refers to the series of corresponding ranks. The Gini coefficient of i th source of income, G_i , can be expressed as

$$G_i = \frac{2}{n\mu_i} \text{cov}(y_i, r_i)$$

where y_i and r_i refer to the series of incomes from the i th source and corresponding ranks, respectively.

The average size of the farm household in the study region is 4.6. The average cultivable land area per farm is 2.2 hectares, with 68.2% of the land dedicated to cash crops, 18.2% to food crops and 13.6% to forage crops. On average, each farm household owns a pair of cows and a buffalo.

The average annual income ($n = 60$) from farm households across the study region is Rs 57 600. The data show that cash crops account for 52.9% of mean per capita household income; food and forage contribute 9.7%; livestock contributes 14%; while off-farm activities account for 23.5%.

We worked out the source income weight which describes relative contribution from various sources to the total farm income (Table 15.1). The results indicated that the source income weight for livestock increased from 0.22 in a normal year to 0.23 in a drought year. Similarly, source income weight for non-farm increased from 0.21 in a

Table 15.1. Decomposition of income inequality in smallholder households ($n = 37$) using Gini coefficient for two contrasting years characterized by normal and drought years

Sources	2000–2001 (normal)			2002–2003 (drought)		
	Source income weight	Source Gini	Correlation between source income and total income	Source income weight	Source Gini	Correlation between source income and total income
Tapioca	0.029	0.898	0.16	0.032	0.901	0.20
Banana	0.071	0.941	0.65	0.063	0.936	0.72
Vegetables	0.013	0.940	−0.01	0.013	0.935	−0.03
Turmeric	0.198	0.766	0.56	0.188	0.796	0.57
Tobacco	0.012	0.963	0.30	0.014	−0.471	0.12
Cotton	0.054	0.827	0.49	0.061	0.819	0.59
Non-farm	0.205	0.686	0.71	0.249	0.626	0.75
Livestock	0.222	0.236	0.42	0.229	0.249	0.49
Overall	1.000	0.376	1.00	1.000	0.400	1.00

normal year to 0.25 in a drought year. During drought years, contributions to the total from both livestock and non-farm activities increase compared to field crops like banana and turmeric. Thus, farmers rely more on livestock and non-farm activities during drought than major field crops. The source Gini coefficients for cash crops like banana and vegetables are highest, indicating that the cash crops are the major source of income inequality among the smallholder farmers.

15.4 ENSO Response Analysis

We used water level records (1997–2002) from 47 control bore wells throughout the Coimbatore district to map the spatiotemporal variability (including possible ENSO influences) of groundwater levels. ENSO phases were categorized based on 5-month running means of spatially-averaged SST anomalies in the Niño 3.4 region of the tropical Pacific (Sittel 1994). A year was considered as ‘warm’ (El Niño) if SST anomalies were >0.5 °C, and ‘cold’ (La Niña) if <-0.5 °C for at least six months, including October–December (Trenberth 1997). Climate data for the past 43 years (1961–2003) for the representative location (Coimbatore, 11° N and 77° E) were used for ENSO response analysis.

The monthly reference crop evapotranspiration was calculated using the FAO Penman-Monteith equation as described by Smith (2000). The relationship for reference crop evapotranspiration is as follows

$$ET_0 = \frac{0.408\Delta(Rn - G) + \gamma \left(\frac{900}{T + 273} \right) U2(ea - ed)}{\Delta + \gamma(1 + 0.34U2)}$$

where ET_0 = reference crop evapotranspiration (mm day^{-1}), Rn = net radiation at the crop surface ($\text{MJ m}^{-2} \text{day}^{-1}$), G = soil heat flux ($\text{MJ m}^{-2} \text{day}^{-1}$), T = average air temperature (°C), $U2$ = wind speed measured at 2 m height (m s^{-1}), $(ea - ed)$ = vapor pressure deficit (kPa), Δ = slope of the vapor pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$), γ = psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$), and 900 = conversion factor.

Crop evapotranspiration for banana, maize and short duration vegetables was calculated using a series of recommended crop coefficient values (K_c) to determine ET_{crop} from reference evapotranspiration (ET_0), as follows:

$$ET_c = K_c ET_0$$

Monthly irrigation requirements conditioned by ENSO phases for all the crops were calculated assuming 75% of the mean rainfall as effective rainfall. The soil type considered for the calculation of irrigation requirements was an alfisol with a total water holding capacity of 140 mm per meter depth. At the start of each simulation, the initial soil moisture content was assumed to equal 50% of the total water holding capacity of the soil profile.

15.5 Spatiotemporal Variability in Water Table Levels

We observed considerable variation in water levels (meters from the surface). In about 40% of the total area in the district, the water table was lower than 15 meters. Generally, the water table is lowest during the March–May pre-monsoon period, due to a lack of recharge and the use of groundwater for irrigation during the dry season. Monsoonal recharge during winter (December–January) causes the water tables to rise, in spite of substantial withdrawals for irrigation.

The observed variation in groundwater levels across the district is associated with interannual rainfall variability. Figure 15.2 illustrates the spatial pattern of water tables in the Coimbatore district in two contrasting years. Due to high rainfall, the December water table was substantially shallower in 1998 than in 2002. The total rainfall received during summer and winter monsoon seasons of 1998 (2002) was 567 mm (385 mm). The years 1998 and 2002 are classified as La Niña and El Niño, respectively.

15.6 ENSO, Rainfall and PET

Some of the observed rainfall variability in the study region is associated with the ENSO phenomenon. Our rainfall analysis showed that on average, summer monsoon (June–September) rainfall was 18% lower during warm than during cold ENSO years (Table 15.2). Conversely, mean winter monsoon (October–December) rainfall was 40% greater during warm than during cold ENSO years (Fig. 15.3a), leading to increased

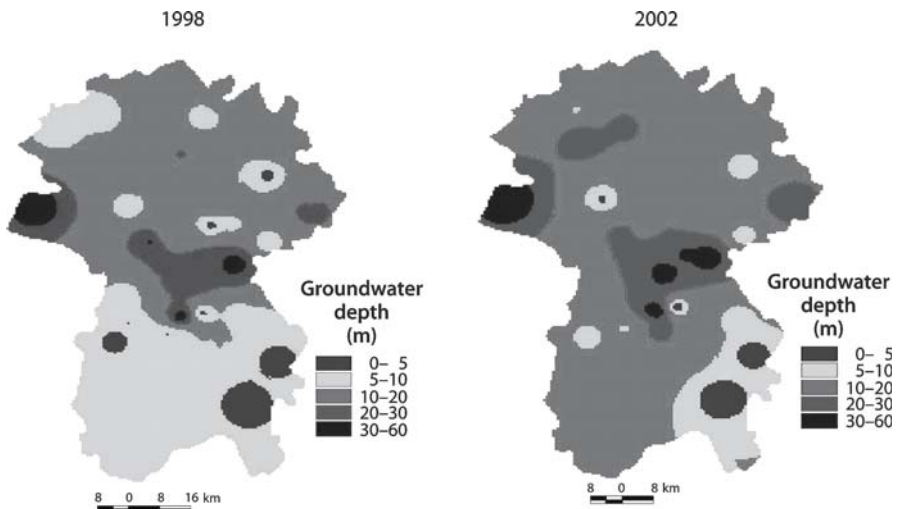
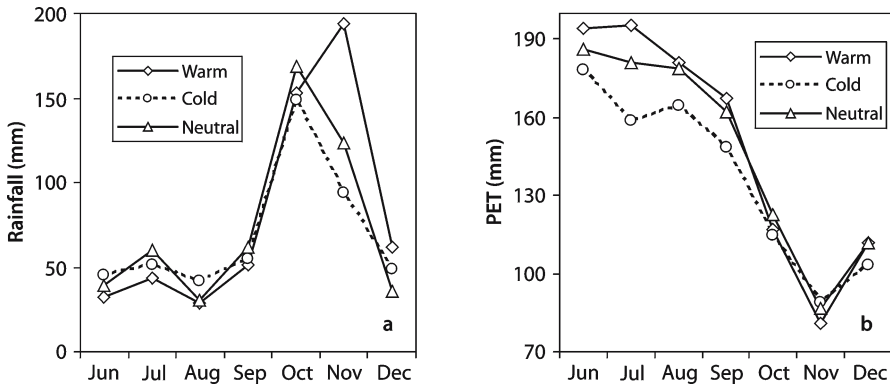


Fig. 15.2. Spatial variation in groundwater table depth (m below the surface) in December during an illustrative high (1998) and low (2002) rainfall year, Coimbatore district, Tamil Nadu, India

Table 15.2. Water balance components for irrigated maize

Particulars	Warm	Cold	Neutral
Effective rainfall (mm)	161	196	198
ET_{crop} (mm)	640	562	615
Total gross irrigation requirement (mm)	600	450	500
Irrigation efficiency (%)	77	83	82

**Fig. 15.3.** Average monthly rainfall (a) at Coimbatore and potential evapotranspiration (PET) (b) in different ENSO phases

groundwater recharge. In seasons of low summer monsoon rainfall during warm ENSO years, potential evapotranspiration increased by 0.8 mm day^{-1} (Fig. 15.3b), indicating higher irrigation requirement. Calculated October–December potential evapotranspiration did not vary significantly among the ENSO phases.

15.7 Crop Evapotranspiration and Irrigation Requirement

15.7.1 Maize

We calculated the crop evapotranspiration (ET_c) and irrigation requirement for a maize crop grown during the summer monsoon (June–September; *kharif*) in the study region. The calculations were based on a 120-day maize cultivar grown under irrigation in a medium-deep alfisol with available water holding capacity of 140 mm. The cropping season starts during the first week of June and ends during the last week of September. Average climatic parameters from warm, cold and neutral ENSO years were used for calculating irrigation requirement. Consistent with local practices, 50 mm of irrigation were assumed whenever the available soil moisture fell below 50% of capacity.

During warm phases calculated crop evapotranspiration increased on average by 14% resulting in a need for increased irrigation (Table 15.2). Reduced rainfall combined with enhanced evapotranspiration is likely to reduce or even prevent groundwater recharge. Groundwater recharge is not only a consequence of rainfall, but is also associated with water storage in local water harvesting structures like tanks and percolation ponds.

Decadal (10 days) irrigation requirements for a 120-day maize crop increase during warm ENSO years (Fig. 15.4). Therefore, insufficient groundwater recharge is more likely to limit the area under irrigated maize in warm ENSO years. Information about ENSO influence on water requirements and potential groundwater recharge could prove useful for improving crop selection and irrigation management decisions during the dry season (February–May) following the winter monsoon. Advance knowledge of likely shortfalls in water availability would enable farmers to reduce their risk exposure by scaling back their investments in irrigated crops. During the summer monsoon, preparing for supplemental irrigation could further reduce the risk of crop failure in warm ENSO years. Modifications of agronomic practices based on anticipated climate conditions offer some scope for risk reduction and increasing groundwater recharge (Jolly et al. 1989) in semi-arid environments.

15.7.2

Cropping Systems

In an attempt to quantify the crop evapotranspiration and irrigation requirement, we examined the major irrigated cropping systems of the region. Specifically, we investigated the water and irrigation requirements for banana, summer maize (June–September), first vegetable crop (June–August), winter maize (December–April) and a second vegetable crop (March–May). Monthly irrigation requirement was calculated assuming an effective rainfall of 75% with an irrigation efficiency of 70%.

Our calculations show that maximum total crop evapotranspiration and irrigation requirements occur during March and August (Fig. 15.5). During August critical stages

Fig. 15.4. Decadal water requirement of irrigated maize (120 days duration) under various ENSO phases

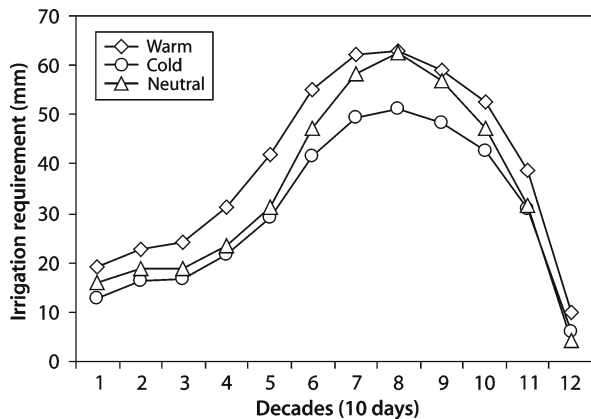
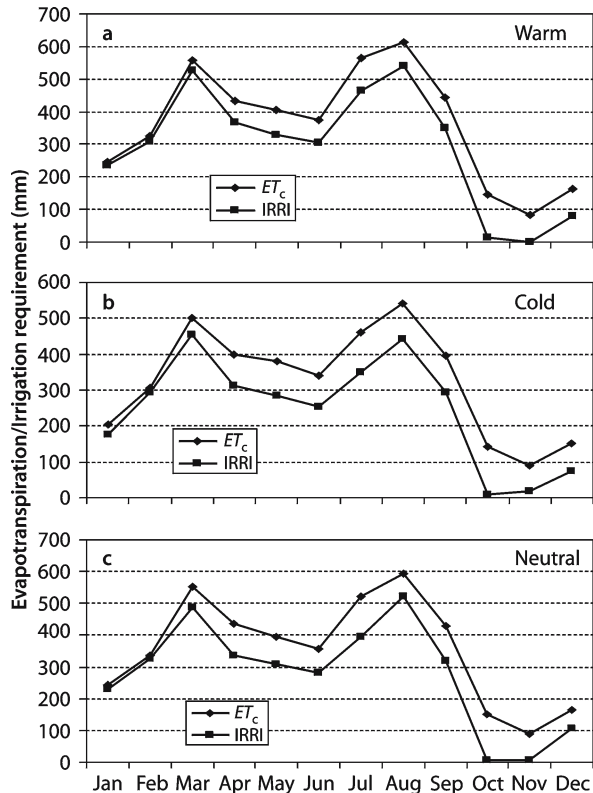


Fig. 15.5. Monthly crop evapotranspiration and irrigation requirement (mm) under ENSO phases; a warm; b cold; c neutral



of water requirement coincide both for summer monsoon maize and vegetables. The long-duration banana is also in the late development/bunching stage requiring maximum water. Considerable variation in crop evapotranspiration and irrigation requirement was evident across the ENSO phases (Table 15.3). The total annual crop evapotranspiration under the warm ENSO phase was 11% greater than during the cold phase. Average annual irrigation requirement for the cropping systems in warm ENSO years was 16% greater than in cold ENSO years. Irrespective of the ENSO phase, bananas account for about 42–43% of the total annual evapotranspiration, and consume 40% of the total irrigation requirement for all the crops.

15.7.3 Crop Area Decisions Based on ENSO Phases

In order to maximize farm gross margins, we constructed a linear programming model that identifies optimum allocation of land area subject to land and water availability constraints under each of the three ENSO phases. The model is formulated as:

Table 15.3. Evapotranspiration (mm) and irrigation water requirement (mm) of crops for southern peninsular India

Crop	Duration (d)	Warm ENSO	Cold ENSO	Neutral
Crop evapotranspiration (mm)				
Banana	360	1 857	1 690	1 846
Vegetable-1	90	603	515	557
Summer maize	120	699	615	673
Vegetable-2l	90	599	552	588
Winter maize	120	599	538	595
Total		4 359	3 912	4 270
Irrigation requirement (mm)				
Banana		1 411	1 206	1 346
Vegetable-1		511	411	468
Summer maize		549	438	498
Vegetable-2		521	451	486
Winter maize		529	455	525
Total		3 521	2 960	3 323

$$\max y = \sum_{j=1}^n C_j X_j$$

such that

$$\sum_{j=a}^n a_{ij} X_j \leq b_i \text{ for all } i = 1 \text{ to } m$$

and

$$X_j \geq 0 \text{ for all } j = 1 \text{ to } n$$

where

- X_j = level of the j th farm activity, such as the area of banana cultivation, for all $j = 1$ to n , where n denotes the number of possible activities (five in our case study);
- C_j = the forecasted gross margin of a unit of the j th activity (e.g. Rupees per hectare);

- a_{ij} = the quantity of the j th resource (e.g. land area and water availability on monthly basis) required to produce one unit of the j th activity, for all $i = 1$ to m , where m denotes the number of resources; and
- b_i = the amount of the i th resource available (e.g. land area and water availability).

The aim of the optimization is to find the land allocation (defined by a set of activity levels $X_j, j = 1$ to n) that has largest possible total gross margin Y , without violating any of the fixed resource constraints.

Variable costs, cost of cultivation, yields and prices of banana, maize and vegetables used in the linear programming model were collected from a sample of 37 farmers. Monthly irrigation water requirements ($m^3 ha^{-1}$, Fig. 15.6) and farm-level water availability (m^3 , Fig. 15.7) across all ENSO phases were estimated by the model. The water requirement of 1 ha banana was on average 17.0% higher during warm ENSO phase ($14\ 110 m^3$) than during the cold phase ($12\ 059 m^3$).

Farm-level water availability was measured in a case study farm with 3 hectares of land. During 2003, daily water discharge from all sources was measured using a parshall flume at the delivery point near the water source. Water availability for the warm and

Fig. 15.6. Monthly irrigation requirement of crops (banana, vegetable-1, summer maize, vegetable-2 and winter maize) considered in the water allocation and crop area decision; a warm; b cold; c neutral

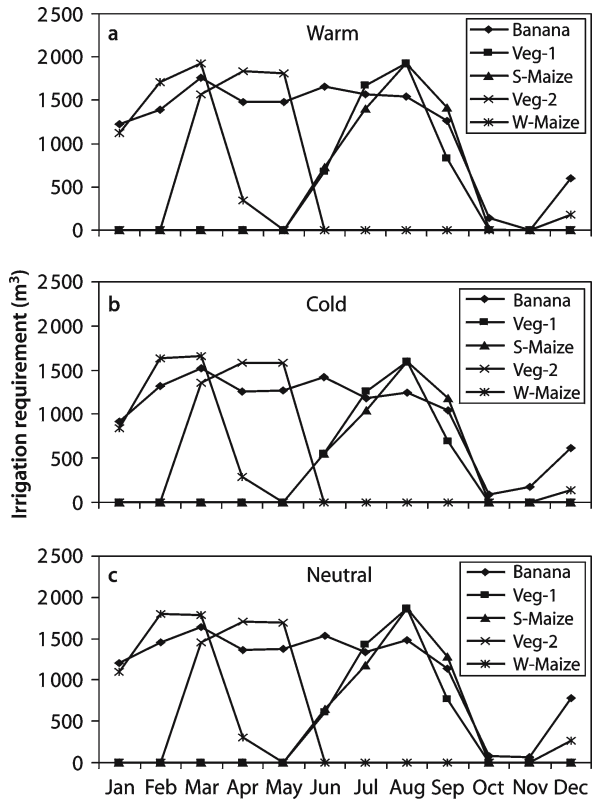
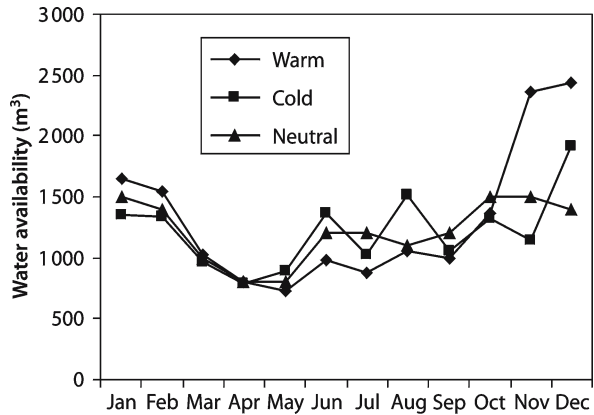


Fig. 15.7. Farm-level water availability under various ENSO phases



cold ENSO phases was estimated by applying the percent increase or decrease in average rainfall associated with the particular ENSO phase to the measured 2003 water discharge. The resulting estimate of annual water availability was 15 816 m³ in warm ENSO years, and 14 600 m³ in cold ENSO years. The higher water availability in warm ENSO years was due to above-average rainfall during October, November and December. However, June to September water availability was highest in cold ENSO years.

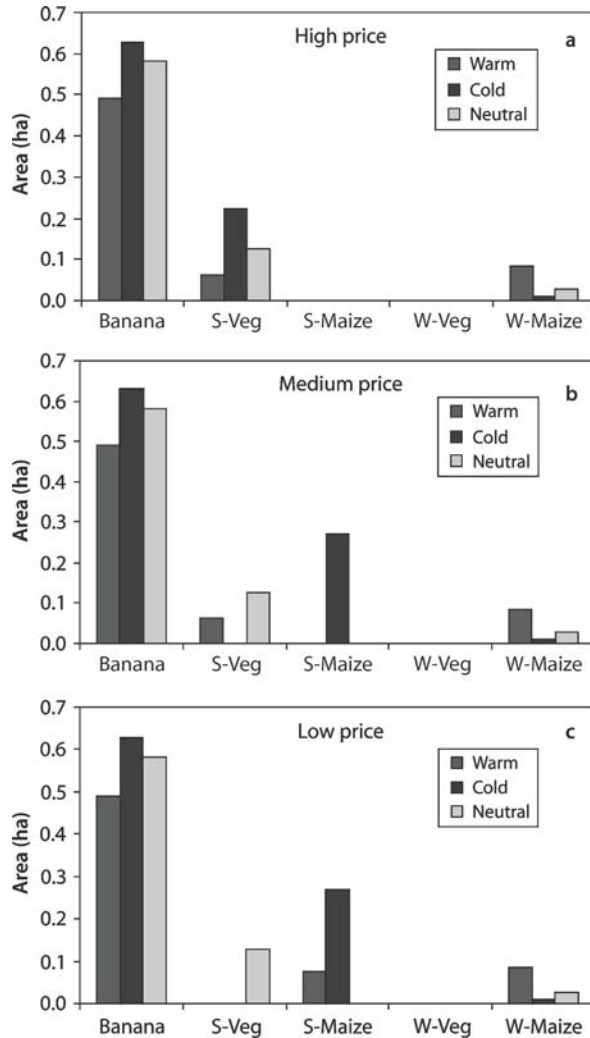
The linear programming model assumes that farmers are indifferent to risk and select farm plans based solely on their economic performance. The model also accounts for constraints such as irrigation requirements. For this case study we assumed that the total land available for irrigation is 3 ha.

The model predicted considerable shifts in land allocation to various crops depending on ENSO phases (Fig. 15.8). However, market price scenarios did not influence optimal land allocation among the ENSO phases. Based on the optimal solution, a risk neutral farmer would reduce the total area under irrigation to 0.63 ha in a warm ENSO year, and increase the irrigated area to 0.91 ha in a cold ENSO year. ENSO phase could also influence the area dedicated to banana substantially. Maximizing gross margin would only be possible if about 0.50 ha of land area was allotted to banana. The total expected gross margin in a 3 ha farm from irrigated crops is Rs 48 109, Rs 63 536 and Rs 56 418 under warm, cold and neutral ENSO phases, respectively (Fig. 15.9). The greater area under irrigation during cold ENSO year is due to comparatively higher farm-level water availability resulting from increased rainfall and reduced crop evapotranspiration.

15.8 Conclusions

Interannual rainfall variability exerts considerable influence on water resources. Groundwater resources in southern India are exploited in order to buffer production systems in this part of the semi-arid tropics against such variability. The use of ex-

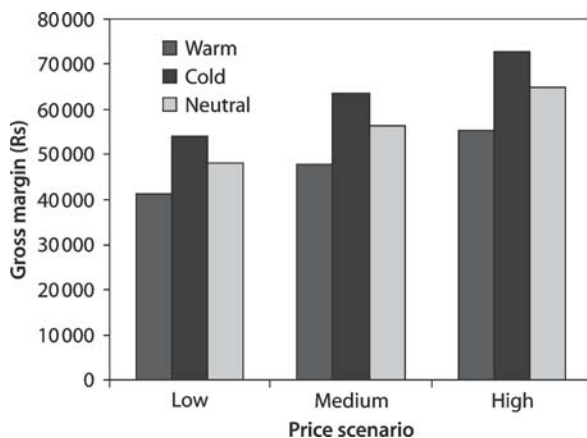
Fig. 15.8. Area under irrigation for various crops conditioned by ENSO phases and price scenarios; **a** high price; **b** medium price; **c** low price



exploitation of groundwater for irrigation has been an effective means of coping with the region's highly variable climate, but now appears that this resource use has reached unsustainably high levels. Opportunities exist to better manage these water resources through appropriate use of climate information, resulting in improved economic performance within a more sustainable production system.

Our results demonstrate that there is opportunity to use information about ENSO and its influence on rainfall and groundwater recharge to better manage irrigated crop production systems, despite the rather modest prediction skill from observed ENSO phases. There may be opportunity to improve ENSO predictions before the onset of the summer monsoon through ensemble SST forecasting. There is also a need to further advance methods for using climate information, and to develop effective exten-

Fig. 15.9. Gross margin (Rs) from irrigated area of a 3 ha farm under ENSO phases and price scenarios



sion programs to support this type of application, which build on the success of regional and village-level stakeholder meetings conducted as part of this work.

Acknowledgements

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Linking Corn Production, Climate Information and Farm-Level Decision-Making: A Case Study in Isabela, Philippines

W. L. de los Santos · F. P. Lansigan · J. Hansen

16.1

Introduction

Corn is the second most important crop in the Philippines in terms of total area planted and overall value next only to rice. Yellow corn is the most important corn type in the Philippines, and is primarily used as feed especially for poultry and swine. In 2003, more than 844 885 ha of agricultural land in the Philippines were planted to yellow corn.

Isabela is the top corn-producing province in the Philippines contributing 17% or 536 353 tons of the country's total yellow corn production in 2003. It is located in the northeast region of the country and is about 10 hours drive north of Manila. Corn is grown rainfed in lowland, upland, and even in riverine or flood-plain areas along the Cagayan River in Isabela. Monocropping of corn is predominantly practiced in Isabela, and there are two cropping seasons per year – wet season cropping from May to August and dry season cropping from November to February. A total of 146 965 ha were planted to yellow corn in the province in 2003. Average yield of yellow corn was 3.65 tons per hectare ($t\ ha^{-1}$) in 2003 which was comparatively higher than the national yellow corn yield average of $3.03\ t\ ha^{-1}$. Most of the corn type being produced in the province is yellow corn which accounted for 95% of the total corn produced in the province (Lansigan et al. 2001).

The climate in the agricultural region of Isabela has historically no pronounced dry or wet seasons but relatively dry in the first half of the year and wet during the second half. Average rainfall is 1 844 mm per year, mean temperature is 29 °C and relative humidity is 66% (PAGASA 2000). In general, the climate and the vast plains of Isabela are suitable for corn production.

Improvements in our understanding of interactions between the atmosphere and its underlying sea and land surfaces, advances in modeling the global climate system, and the substantial investment in monitoring the tropical oceans now provide a degree of predictability of climate fluctuations at a seasonal lead time in many parts of the world (Hansen 2002). Climate information influenced corn production activities and decisions. Through time, corn farmers have developed management practices and adaptation measures to cope up with climate variability. This chapter examines the perception of corn farmers and of the agricultural extension workers on the links between corn production, climate forecast information, and farm-level decision-making in two different corn agro-environments in the Isabela province of northern Philippines.

16.2 Methodology

16.2.1 Case Study Sites

Isabela province is located in the northernmost part of the Philippines (Fig. 16.1). Two corn-producing municipalities were identified for the case study representing different agro-environments, namely: (1) the lowland corn areas in the low-lying, flood-prone areas in the town of Naguilian; and (2) the upland corn areas in the nearby mountainous municipality of Benito Soliven. The two towns are located about 15 kilometers apart. Naguilian (121°50' E latitude and 17°60' N longitude, elevation 40 m) has low-lying corn-growing areas located near the Cagayan River – one of the most important rivers in northern Philippines. It has a land area of 170 km² and a current population of 26 131. On the other hand, Benito Soliven (121°60' E latitude and 17°00' N longitude, elevation 98 m) is a mountainous corn-growing municipality. It has a land area of about 187 km² and a population of 22 146.

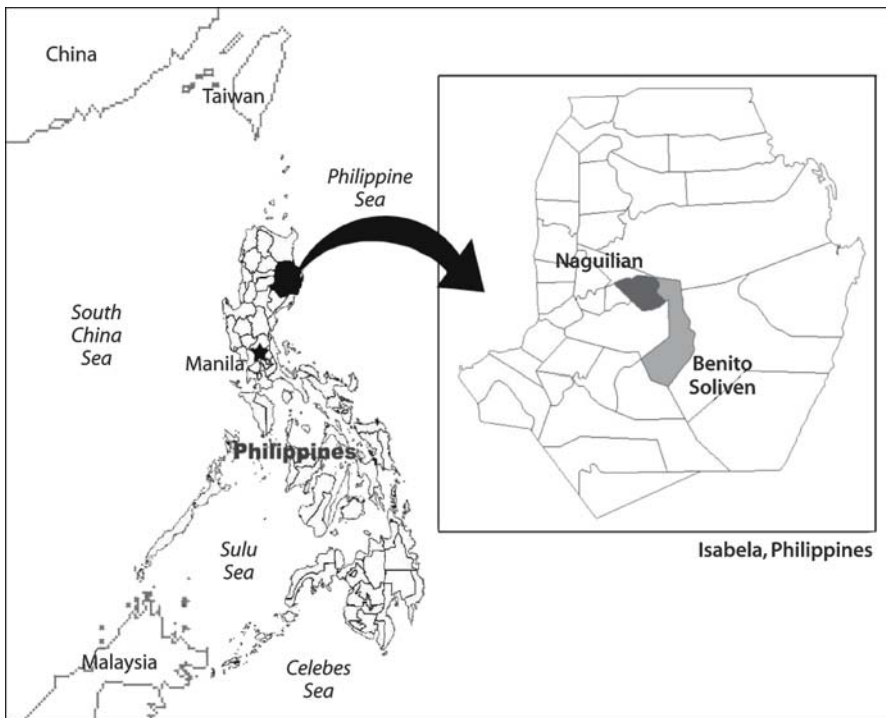


Fig. 16.1. Map showing the location of the municipalities of Naguilian and Benito Soliven in Isabela Province, Philippines

16.2.2

Data Collection

A number of activities and decisions in corn production are influenced by available climate information in the area. These include the date of land preparation and planting, choice of corn cultivars to grow, scheduling of applications of fertilizer and irrigation water, and harvesting. A necessary step in promoting agricultural use of climate information, or in assessing its value, is to gauge user perceptions concerning the use of that information (Stern and Easterling 1999). Thus, to assess the perceptions of corn farmers in Isabela province on the links between corn production, climate forecast information, and farm level decision-making, a survey involving 60 farmers (30 from each municipality) and 40 agricultural extension workers was performed from November to December 2003. The study used personal interviews, and a structured survey questionnaire to interview corn farmers and local agricultural officers and extension workers.

16.3

Results and Discussion

A typical corn farmer surveyed in Isabela, Philippines is male, 43 years old, has received high school education, and has about 18 years of corn farming experience. He owns about 2 hectares of relatively flat, agricultural lands that is solely planted to corn. An unpaved feeder road connects his production site to the market. On the average, his farm is about 6 km away from the nearest market and about 7.6 km away from the nearest Department of Agriculture extension office. On the other hand, a typical agricultural extension worker or agent interviewed during the survey in the province is 40 years of age, has received a university or college degree, and has 14 years of experience in agricultural extension work.

According to the farmers surveyed, corn is primarily grown in Isabela province because of its existing market, lower manpower requirement compared to other crops, and general suitability to the area. Corn farmers raise yellow hybrid corn twice a year. The average corn yield is 4 330 kg ha⁻¹ during wet season cropping (May–August), and 4 719 kg ha⁻¹ during dry season cropping (October–January).

16.3.1

The Impact of Climate Variability on Corn Production

Countries in Southeast Asia and the Pacific region, together with Australia, experience the highest rainfall variability in the world (Nicholls 1997). El Niño events are manifested in the Philippine local climate by drier than normal weather conditions which could last for one or more seasons, causing dry spells or even drought in many parts of the country. These dry weather conditions are caused by suppressed tropical cyclone activity in the western equatorial Pacific, weak monsoon activity characterized by “breaks”, and the delayed onset of or early termination of monsoon rains (PCARRD 1999). In agriculture, shortage of water has caused serious damage to farmlands. The

Philippine Crop Insurance Corporation (PCIC) reported that claims of losses for rice in the Philippines in 1997 amounted to U.S.\$280 000 while corn claims amounted to U.S.\$480 000.

Compared with the El Niño event, which is characterized by unusually warm ocean temperatures in the equatorial Pacific region, La Niña is characterized by unusually cold ocean temperatures the equatorial Pacific region. This condition brings greater than normal amounts of cloudiness and rains over the warm waters of the western Pacific including the Philippines. During the last half century, there have been about 10 to 11 weak and strong El Niño events which has brought adverse socio-economic impacts in the Philippines. The 1982–1983 El Niño event caused about U.S.\$500 million damages to the Philippines as compared to the U.S.\$13 billion global damage.

In northeastern Philippines, Dammay (2003) reported that weather disturbances in the form of flooding and drought are the primary contributors to corn production losses. Based on farmers' reports during the past crop years, typhoon damage can cause a 70% yield loss while flood occurrence can wipe out an entire corn crop. Drought can result in a 50–70% yield loss. However, for the farmers surveyed in Isabela province, the 1997–1998 El Niño occurrence resulted in an average yield loss of 1 276 kg ha⁻¹ of corn harvested representing about 27% of the seasonal corn yield per hectare. The survey also showed an average loss of 700 kg ha⁻¹ of corn during the succeeding 1998–1999 La Niña event which represents about 16% yield loss – a lower level of damage compared to the earlier drought period.

In the Asia-Pacific region, El Niño event is often associated with clear skies and droughts, while La Niña episode is related to overcast skies and flooding (Centeno et al. 2000). As regards the El Niño and corn production, majority of corn farmers surveyed in Isabela have a negative view of its effects on corn production as shown in Table 16.1. However, during La Niña, the topography of the corn-growing municipality has a significant effect on the perception of the farmers interviewed with regard to their views on the effects of La Niña on corn production. Farmers of Benito Soliven – a mountainous municipality, viewed La Niña favorably since it brought adequate moisture – thus greater yield to its rainfed production system. On the other hand, majority of farmers from Naguilian, a lower elevation municipality that is flood-prone during typhoon seasons, took the negative view when it comes to La Niña occurrence.

Table 16.1. Farmers' perception on the effect of El Niño and La Niña events on corn production in Isabela, Philippines

Municipality	Good (%)	Bad (%)	No effect (%)	Not aware of (%)
Effect of El Niño				
Benito Soliven	0	90	0	10
Naguilian	7	90	3	0
Effect of La Niña				
Benito Soliven	90	0	0	10
Naguilian	7	83	10	0

These survey results are also consistent with the general pattern of observations from Isabela corn farmers during the 1997–1998 El Niño event and the succeeding 1998–1999 La Niña episode. During the 1997–1998 El Niño period, actual data in Isabela province showed that it lost 218 983 metric tons of corn valued at U.S.\$36 million due to drought. During the succeeding 1998–1999 La Niña episode, typhoons and flash floods destroyed 10 738 hectares of corn incurring a production loss of 10 976 metric tons (Lansigan et al. 2001).

16.3.2

Climate-Related Information Currently Accessible in Isabela

Table 16.2 shows the sources of climate-related information among agricultural extension workers and corn farmers in Isabela province. Among government agricultural extension workers, the primary source of climate-related information is the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) – the government meteorological agency. This is followed by television and radio, print media (e.g. newspapers), and fellow extension agents. All Philippine agricultural extension workers and agents received university or college degrees which suggest their “comfort in accessing” meteorological bulletins. This is not the case for farmers – a majority of whom did not have university- or college-level education. Farmers derive their climate-related information from mass media – mainly from radio and television broadcasts, and also from their fellow farmers. This situation makes it critical for climate and agriculture policy makers to focus on the commonality among agricultural workers – both extension agents and farmers- which is the importance of radio and television as a means for effective dissemination of climate information and forecasts.

16.3.3

Impact of Seasonal Climate Forecast Information on Decision-Making

Blench (1999) reported that forecasts are only relevant to producers that conform to the following profile: large and specialized operations, high in resources like education, and dependent on rainfall. In the case of Isabela, forecasts were important since the corn production system is generally rainfed. Besides the relatively rich and edu-

Table 16.2. Sources of climate-related information among agricultural extension workers and corn farmers in Isabela, Philippines

Source	Agricultural extension workers (%)	Farmers (%)
PAGASA	42	–
Agricultural extension workers	12	3
Farmers	–	43
Publications	18	3
Radio and television	28	51

cated farmers, even farmers with small to large crop hectarage, and of different academic backgrounds have signified their need for climate forecasts aside from the relatively rich and educated farmers.

The survey also noted that all farmers interviewed were not willing to change crop species even with advanced climate information. What they were willing to modify include the choice of corn cultivars to grow, planting date, and time of fertilizer application. Capital, the cost of farm inputs, the previous season's price of corn grains and their perceived seasonal climate outlook have equal influence on Isabela corn farmers' production decisions.

16.3.4

Forecast Information of Greatest Value to Corn Production

Table 16.3 shows that agricultural extension workers view the onset of the rainy season, duration of rainy days, rainfall distribution, and drought and typhoon occurrence as equally important climate information that they would like to request to be made available to them. On the other hand, farmers' most requested information is the duration of rainy days. This information is important in scheduling land preparation and planting. While the Philippines experiences, on the average, about 20 typhoons annually and Isabela is along the typhoon belt, there was very little need for typhoon-related information since it is considered a regular occurrence in Isabela (PAGASA 2000). Farmers and extension workers are quite satisfied with the advance typhoon warnings and advisories of PAGASA. However, majority of the extension agents and all of the farmers interviewed would like a lead time of at least 1–2 weeks for their advanced climate-related information to be significantly useful in corn production. This lead time is seen as an adequate enough period to adopt or make the needed adjustments or decisions on corn production-related activities such as planting and fertilizer application.

16.3.5

Effective Medium for Communicating Climate Forecast Information

Communicating uncertainty in climate forecasts is one of the major challenges in bringing forecast information to end users (Phillips et al. 2000). This is further complicated by regional dialects, many of which are limited in expression of abstract concepts which are often associated with climate prediction and forecasts. Climate forecast information containing relevant information leading to improved production decisions must reach the end users – the corn farmers, well in advance so that a farm-level decision can still be made. Both educated farmers (those who receive high school education and above) and less-educated farmers (those who have received elementary education only) have indicated their preference to receive climate forecast information primarily through mass media followed by personal contacts with extension agents. For policy makers, mass media, especially television and radio can be a cost-effective means of communicating climate-related information (Table 16.4). However, translating imperfect ENSO-related climate forecasts into information useful for improved farm-level decision-making remains a challenge that needs to be addressed. Climate forecast information should be translated to layman's terms as farmers and

Table 16.3. Type of climate-related information requested by agricultural extension workers and corn farmers in Isabela, Philippines

Information requested	Agricultural extension workers (%)	Farmers (%)
Onset of rainy season	20	25
Duration of rainy days	20	31
Rainfall distribution	20	26
Occurrence of typhoon	20	1
Occurrence of drought	20	17
1–2 weeks information lead time	74	100

Table 16.4. Corn farmers' perception on effective medium of delivery of climate-related information in Isabela, Philippines

Source of information	Educated farmers (%)	Less-educated farmers (%)
Through mass media (radio, television, and newspaper)	55	56
Through personal contacts with extension workers	45	44

the extension workers often perceive these forecasts as absolute values and do not interpret the information in probabilistic sense. This presents an important consideration in implementing intervention strategy for farmers and extension workers to better appreciate and increase awareness of the value of climate forecasts to corn production.

16.4 Summary and Conclusions

El Niño event and the drought it brings is viewed by majority of Isabela corn farmers to have a far greater negative effect on their production system compared with La Niña episode since most of the corn areas are rainfed. For the farmers surveyed in Isabela province, the 1997–1998 El Niño occurrence resulted in an average yield loss of 1 276 kg ha⁻¹ of corn representing about 27% of the seasonal corn yield per hectare. The survey also showed an average loss of 700 kilograms of corn per hectare during the succeeding 1998–1999 La Niña event which represents about 16% yield loss. Farmers growing corn in mountainous communities such as in the municipality of Benito Soliven view La Niña occurrence as something beneficial to corn production considering their rainfed production system. Meanwhile, farmers in low-lying communities such as in Naguilian look at La Niña as something negative that can bring with it floods that can destroy their crops.

Agricultural extension agents derive their climate-related information primarily from the national meteorological agency (PAGASA) while farmers rely on television

and radio for their advanced climate/weather information. Extension agents were not the main source of climate-related information for farmers. All farmers interviewed were not willing to change crop species even with advanced climate information. However, they were willing to modify only the choice of corn cultivars to grow, planting date, and time of fertilizer application.

Capital, the cost of farm inputs, the previous season's price of corn grains and their perceived seasonal climate outlook have equal influence on Isabela farmers' corn production decisions. Moreover, farmers' most requested information to be made available is the duration of rainy days. Both agricultural extension agents and farmers agreed on 1–2 weeks as the most ideal lead time for the delivery of climate forecast information. Television and radio broadcasts were the preferred medium for the delivery of climate forecast information. However, translating imperfect ENSO-related climate forecasts into information useful for improved farm-level decision-making remains a challenge that needs to be addressed. There is a need to translate the climate information and forecasts in terms of what the corn stakeholders can interpret and use correctly to guide decision-making in corn production system.

Acknowledgements

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Use of ENSO-Based Seasonal Rainfall Forecasting for Informed Cropping Decisions by Farmers in the SAT India

V. Nageswara Rao · P. Singh · J. Hansen · T. Giridhara Krishna · S. K. Krishna Murthy

17.1

Introduction

Dryland agriculture in India is practiced on 97 million ha of the cultivated area that supports 40% of the human population and 60% of livestock population by producing 44% of the food and fodder requirements. Even if India can achieve the full potential of irrigation in 139.5 million ha, still 75 million ha drylands would continue to depend on rainfall from southwest (SW) and northeast (NE) monsoons, characterized by high rainfall variability that cause most of production uncertainties. Thus dryland agriculture continues to play a crucial role in India's food security. However, productivity gains have been relatively insignificant and risk-averse dryland farmers have to improve agricultural productivity with suitable management options and matching application of farm inputs to maximize crop productivity and income, while minimizing crop failure and input losses against uncertainties of seasonal weather to feed the booming population.

17.2

Advances in Seasonal Climate Forecasting

Sir Walker's early pioneering efforts in making long range forecasting of monsoon rainfall in India, led to several concepts on teleconnection and statistical relations in the field of climate forecasting especially the El Niño-Southern Oscillation (ENSO). Shukla and Paolino (1983) studied relations of Southern Oscillation on possibility of long range forecasting of Indian summer monsoon rainfall. Ropelewski and Halpert (1987, 1996) established better correlation of Pacific Ocean sea surface temperatures (SSTs) compared to Indian Ocean SSTs with rainfall variability in Indian subcontinent which also indicated the skill of October-November-December (OND) seasonal rainfall prediction in southern India. Both these efforts were focused on understanding the ENSO dynamics on slowly varying equatorial ocean temperatures, and established relationships to their manifestations on changing atmosphere and observed climate variability.

Virmani et al. (1982) estimated seasonal rainfall probabilities using statistical models for many locations in the semi-arid India. Gadgil et al. (1999) identified stronger relationship between El Niño years and rainfall in Anantapur compared to all-India summer monsoon rainfall from their analyses on seasonal rainfall from 1911–1998. Stone et al. (2000) demonstrated statistical methods to generate rainfall probabilities of climate forecasts from general circulation model (GCM)-derived southern oscillation index (SOI) phases that are useful inputs for agricultural simulations to derive

management decision options. Predictability of climate at regional scale presents an opportunity to identify feasible alternatives to mitigate the climate risks, improve productivity and food security.

17.3

Advances in Crop Modeling

Comprehensive systems simulation models can simulate the dynamic processes of crop growth and development capturing their dynamic and nonlinear interactions with environmental variables. Agricultural Production Systems sIMulator (APSIM) (Mc Cown et al. 1996) is a cropping systems model suite, which was developed and validated across several environments, especially, in the semi-arid tropics. Hammer et al. (1996) analyzed the skill of seasonal climate forecasting in the management of wheat crop with fixed and tactical decisions of applying N in a highly variable climate to increase profit and minimize risk. Gadgil et al. (1999), through their simulation work on “*Farming Strategies for a Variable Climate*”, anticipated considerable impact of seasonal rainfall forecasting on farm-level decisions of peanut growers in Anantapur using DSSAT. Carberry et al. (2000) demonstrated through a simulation case study that *SOI* contributed skill in improving crop management decisions over two-year rotations in Australia. Using APSIM simulation analyses, Nageswara Rao et al. (2004) showed that intercropping of peanut with short duration (SD) pigeonpea can minimize the risk of crop failure, and verified this concept for two years in farmers’ fields in several villages of Anantapur during the period 1999–2002. APSIM model has been successfully used for climate forecast based agricultural/crop management options across several countries including, India (Gadgil et al. 2002) and Australia (Carberry et al. 2000; Meinke and Hochman 2000; Nelson et al. 2002) to deal with crop systems/management options under varying environmental conditions without much limitations for data requirements. Recent advances in the predictability of seasonal climate and wider adaptability of cropping systems models to simulate crop yields based on seasonal climate forecasts, would provide opportunities for farmers to discuss several management options, before opting for a suitable crop management decision based on their available resources.

17.4

Overall Objective

The overall objective of this study was to identify the skill of seasonal climate forecasts for the region and the value forecast skill for management decisions to minimizing the risk of climate variability on cropping systems’ productivity.

17.5

Specific Objectives

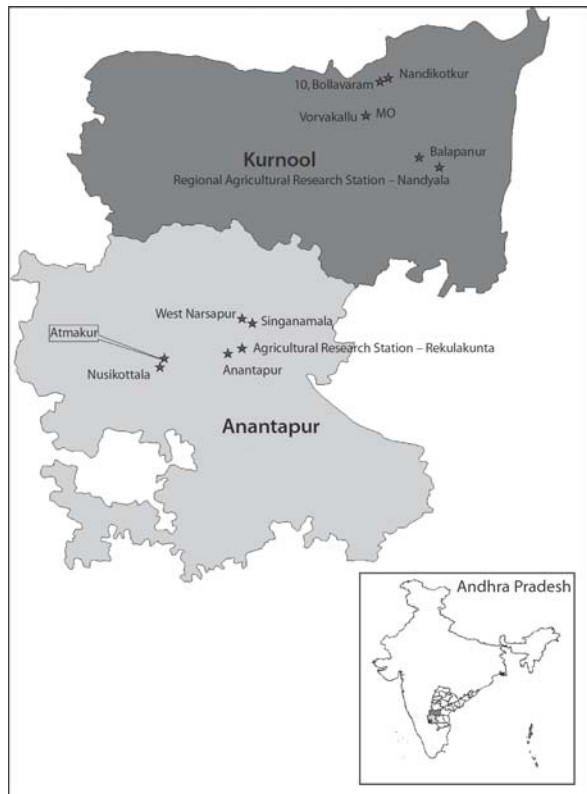
1. To identify the ENSO relationship with seasonal rainfall and crop yields in the scarce rainfall zone of Andhra Pradesh, India.
2. To explore the potential value of seasonal rainfall forecasting for a range of improved cropping decisions.

17.6 Study Area

We consider studying the potential of climate applications in Kurnool and Anantapur in the scarce rainfall zone of Andhra Pradesh state in the southern peninsular India (Fig. 17.1) as farmers in these districts are mostly dependant on dryland agricultural incomes for their livelihoods and are often affected by crop losses and low incomes due to climate variability.

Kurnool district receives an annual rainfall of ≈ 640 mm, ranging from 548 to 668 mm among different agro ecological situations, with a high coefficient of variation indicative of a high climate variability leading to uncertainties in crop production. Total rainfall in the crop season is received during two monsoon seasons (bi-model distribution): southwest (SW) monsoon during June-July-August-September (JJAS) and northeast (NE) monsoon during October-November-December (OND). Early season droughts during SW monsoon often result in first crop failure in this region. Year-to-year rainfall variability (Fig. 17.2, top panel), at the onset of southwest monsoon results in fluctuation in area sown and production of *kharif* sorghum and *mungari* cotton (*Gossypium hirsutum* sp.). Rainfall anomalies during NE monsoon (OND) pe-

Fig. 17.1. Study area and location of project villages in Kurnool and Anantapur districts of Andhra Pradesh, India



riod (Fig. 17.2, middle panel) influence area and production of chickpea and post-rainy sorghum, causing uncertainties of farm-income to resource-poor farmers. Soils in the Kurnool district are largely Vertisols or Vertic inceptisols with varying soil depth ranging from 90 to 150 cm with high clay or clay loamy calcareous soils. These soils can hold plant available soil water (PASW) ranging from 150–240 mm and possess high moisture retention capacities to support post rainy season drought tolerant crops like sorghum, sunflower, chickpea, and safflower are generally grown on stored soil moisture.

Normal rainfall for Anantapur district is low at 564 mm, with rainfall variability ranges from 493 to 593 mm among different agro-ecological situations. Anantapur normally receives 60% of rainfall from SW monsoon (JJAS), 27% NE monsoon (OND) (a bi-modal distribution), and seasonal anomalies especially in SW monsoon (Fig. 17.3, middle panel) influence the productivity of main crop peanut. Length of crop growing season is generally limited between 100 and 135 days by low rainfall and shallow Alfisols. Hence Anantapur typically represents the problems of dry land farming systems in the semi-arid to arid regions. Therefore, it was decided to determine the value of forecast skill for the region to convince stakeholders to utilize seasonal forecasts for crop management decisions.

17.7 Approach

17.7.1 Climate Analyses and Seasonal Prediction

Analyses were carried out to understand the relationships between ENSO and seasonal rainfall variability in the scarce rainfall region, especially with reference to Nandyala as well as Anantapur station weather observations. Records of historical rainfall of Nandyala (1950–2000) and Anantapur (1950–2000) were correlated with sea surface temperatures of the Niño 3.4 region (equatorial Pacific region between 120–170° W and 5° N–5° S as in Fig. 17.4) since 1950–2000.

We used three-month running-mean values of SST departures in the Niño 3.4 regions based on a set of improved homogeneous historical SST analyses (Extended Reconstructed SST-ERSST.v2, Smith and Reynolds 2003). National Oceanic and Atmospheric Administration's (NOAA) official operational definitions of El Niño and La Niña are as follows. El Niño is a phenomenon in the equatorial Pacific Ocean characterized by a *positive* sea surface temperature departure from normal (for the 1971–2000 base period) in the Niño 3.4 region greater than or equal in magnitude to 0.5 °C averaged over three consecutive months. La Niña is described as a phenomenon in the equatorial Pacific Ocean characterized by a *negative* sea surface temperature departure from normal (for the 1971–2000 base period) in the Niño 3.4 region greater than or equal in magnitude to 0.5 °C averaged over three consecutive months. As per these definitions of El Niño and La Niña, years were categorized as given in Table 17.1.

SW monsoon and NE monsoon rainfall for individual years as influenced by ENSO phase were also presented in Fig. 17.5ab, for both stations to visualize the signal for ENSO phase over two seasons in each year with circle indicating El Niño event, and triangle indicating La Niña.

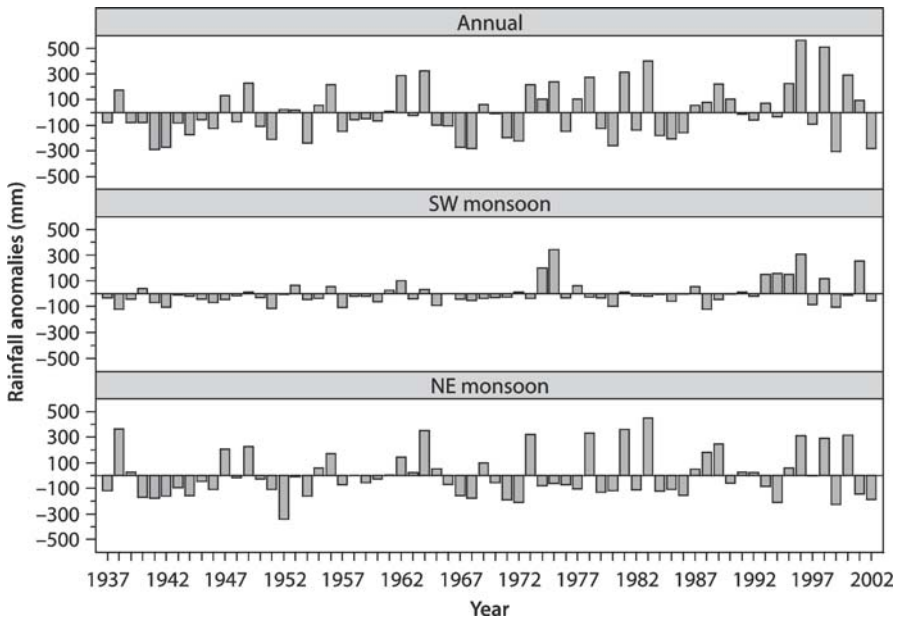


Fig. 17.2. Observed rainfall anomalies of annual, SW monsoon and NE monsoon periods since 1937 at RARS, Nandyala

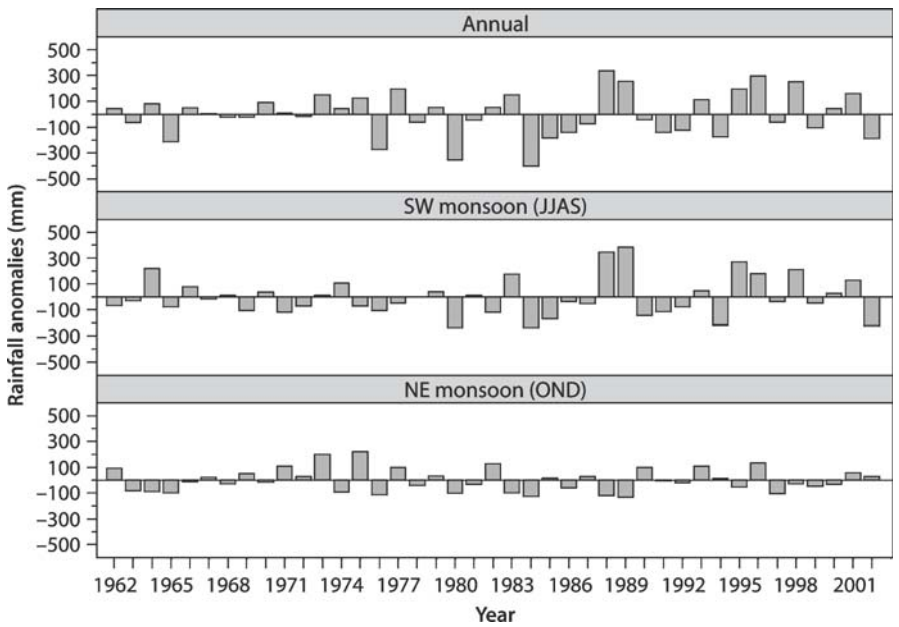


Fig. 17.3. Observed rainfall anomalies of annual, SW monsoon and NE monsoon periods since 1962 at ARS, Anantapur

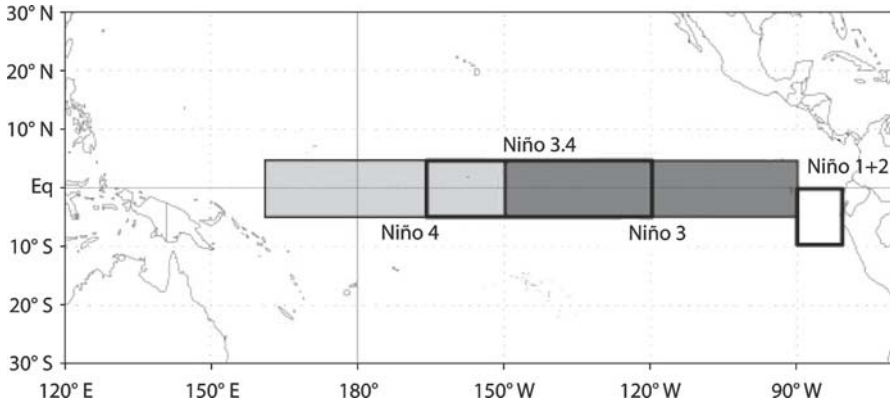


Fig. 17.4. Niño regions on the equatorial pacific as Niño 4 (light gray), Niño 3 (dark gray), Niño 3.4 (intersecting light and dark gray) and Niño 1+2 (empty box) regions

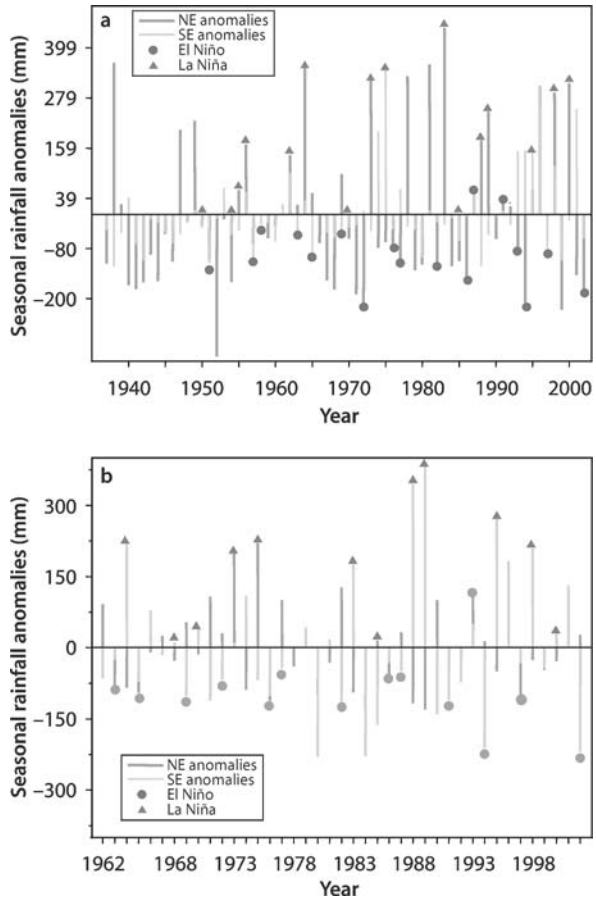
Table 17.1. Year-wise categorization of ENSO phases from 1950 to 2002 based on NOAA’s definition of El Niño and La Niña

ENSO phase	Years (SST anomaly maximum)
El Niño (warm, low SOI)	1951 (0.7), 1957 (1.6), 1963 (1.0), 1965 (1.6), 1969 (0.7), 1972 (2.1), 1976 (0.8), 1977 (0.8), 1982 (2.3), 1986 (1.2), 1987 (1.6), 1991 (1.8), 1993 (0.8), 1994 (1.3), 1997 (2.5), 2002 (1.5)
La Niña (cold, high SOI)	1954 (-1.1), 1955 (-2.1), 1956 (-1.2), 1964 (-1.1), 1968 (-0.9), 1970 (-1.4), 1973 (-2.0), 1975 (-1.8), 1983 (-0.9), 1985 (-1.1), 1988 (-1.9), 1989 (-1.9), 1995 (-0.8), 1998 (-1.6), 2000 (-1.6)
Neutral	1950, 1952, 1953, 1958, 1959, 1960, 1961, 1962, 1966, 1967, 1971, 1974, 1978, 1979, 1980, 1981, 1984, 1990, 1992, 1996, 1999, 2001

Based on ENSO phase, seasonal rainfall (JJAS and OND) was segregated for all years and the distribution of rainfall for each station is shown in box plots (Figs. 17.6 and 17.7) during three phases for Anantapur and Nandyala from 1950–2001.

Ropelewski and Halpert (1996) quantified global precipitation distributions in relation to Southern Oscillation (SO) and observed shifts in the percentiles of rainfall for the Indian subcontinent; with dry seasonal conditions during warm SSTs (low SOI) in the Pacific, and wetter seasonal conditions with cold SSTs (high SOI). Although ENSO is not the only factor influencing monsoon precipitations over the Indian subcontinent (Hastenrath 1987; Shukla and Mooley 1987), the close relationship between the SW monsoon rainfall and the ENSO phases are clearly seen (Fig. 17.6) in case of Anantapur. La Niña years’ median (50%) rainfall is well over total rainfall received (<400 mm) in that of any El Niño year, and more than 75% percentile of normal years. Median difference in rainfall is around 150 mm between El Niño and La Niña events which is crucial in any agricultural situation. While OND rainfall for Anantapur is low, El Niño and neutral years especially have a higher probability to receive more rainfall compared to the cold events.

Fig. 17.5. a JJAS and OND seasonal rainfall distribution of Nandyala as affected by ENSO phase categories from 1950 to 2001; **b** JJAS and OND seasonal rainfall distribution of Anantapur as affected by ENSO phase categories from 1963 to 2001



In case of Nandyala (Fig. 17.7), La Niña years receive higher rainfall with a median <725 mm and approximately 900 mm can be expected in 25% percentile years, while during the El Niño and neutral years, the median remains same, just below 500 mm. In winter months (OND), the median rainfall remains nearly at 100 mm with all phases, but the shift is towards higher rainfall in La Niña years as compared to neutral phase.

17.7.2

Crop Yield Variability in Response to ENSO Phases

Mungari cotton, *khariif* sorghum; peanut/pigeonpea intercrop systems have been the major crops cultivated in Kurnool during the SW monsoon season. Sunflower, chickpea and post rainy season sorghum are the major sequential crops grown during post rainy (NE monsoon) season. We analyzed the distribution of crop yields for each ENSO phase.

Crop yields were grouped based on the categorization of ENSO phases (Table 17.1) since 1950 to 2002. These yields were calculated from observed crop production in each

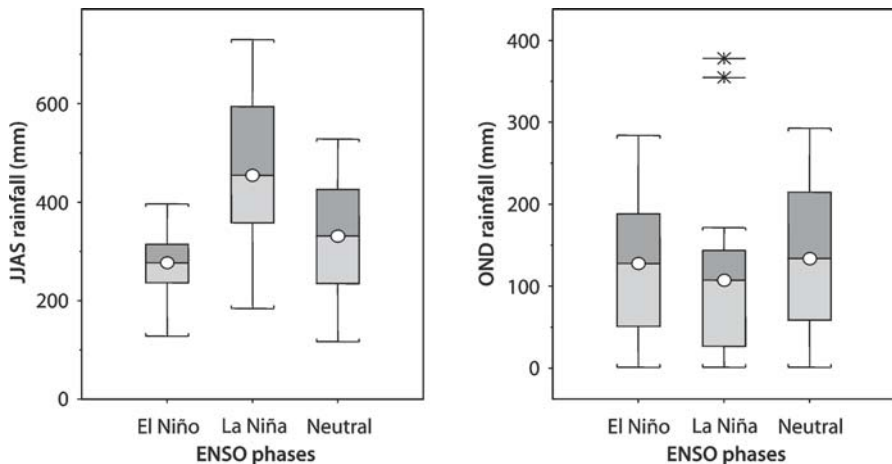


Fig. 17.6. Seasonal rainfall distribution of Anantapur as affected by ENSO phase categories from 1963 to 2001

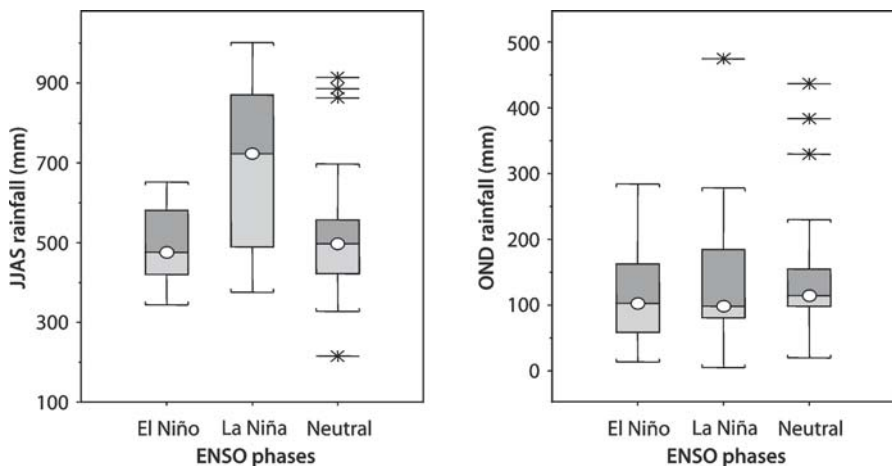


Fig. 17.7. Seasonal rainfall distribution of Nandyala as affected by ENSO phase categories from 1963 to 2001

district. This analysis provides inferences on the performance and likely adaptability of a crop once the ENSO phase is known, based on historically observed yields in different ENSO phases.

Box plots of crop yield distribution in different ENSO phases (El Niño, La Niña, neutral) indicate yield distribution of 25th percentile from bottom of the box (light gray) and 75th percentile to the top of the box (dark gray), with a circle connected by horizontal line in the middle of the box representing median (50th percentile) of the crop yields time series. Bottom whisker cap indicates 10th and top whisker indicates

95th percentile of yield distribution. Horizontal lines with star or circle away from box plots are out-liers in the data representing a skewed distribution (Figs. 17.6 and 17.7).

In Kurnool, kharif sorghum median yield is above (0.75 t ha^{-1}) during La Niña years, and distribution of sorghum yield in this phase ranged from 0.25 to 1.5 t ha^{-1} indicating that good rainfall distribution leads to higher yields in 50% of years and that sorghum yield in neutral years is also good compared to El Niño years (Fig. 17.8). Hence sorghum can be a rainy season crop option except in El Niño years. Contrary to expectations, mungari cotton yielded better in El Niño years compared to neutral or La Niña years, and can be a suitable crop option in El Niño years (Fig. 17.9). Peanut and pigeonpea intercrop system is an obvious choice in light soil areas of Kurnool during La Niña phase as the median yield for both the crops is conspicuously higher and yield addition in this phase is $>250 \text{ kg ha}^{-1}$ (Fig. 17.10ab). Chickpea and rabi sorghum have been two alternate crops for farmers of Kurnool as a sequential post rainy season crop, and both crops have different suitability options. While Chickpea yields were higher in El Niño years, its performance in La Niña is also consistently better than in neutral years (Fig. 17.11a). As opposed to this, sorghum median yields were higher and is a suitable option for this region in La Niña conditions (Fig. 17.11b).

Fig. 17.8. Rainy season sorghum yield as affected by rainfall in ENSO phases during 1950–2001 in Kurnool

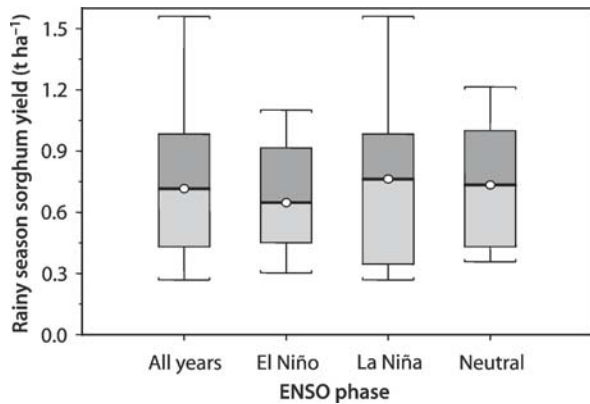


Fig. 17.9. Mungari cotton yield as affected by rainfall in ENSO phases during 1950–2001 in Kurnool

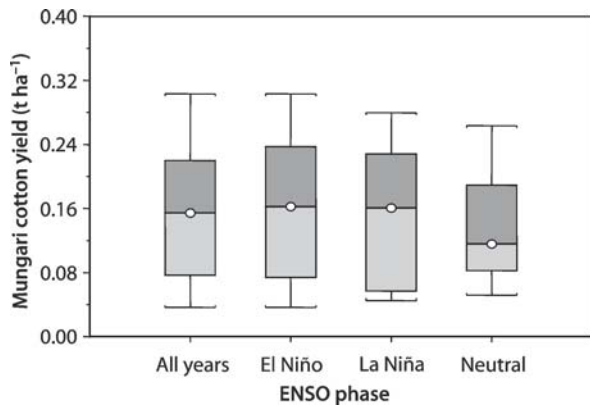
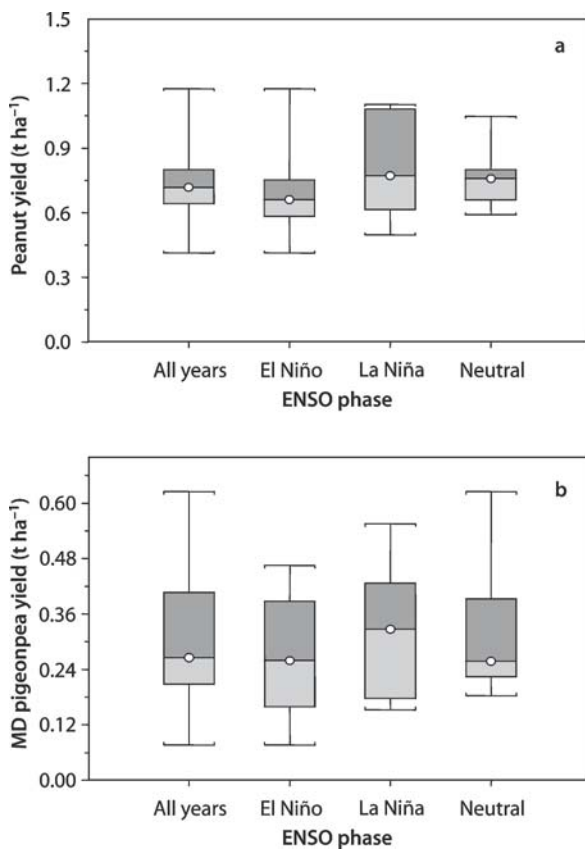


Fig. 17.10. a Peanut yield with intercrop as affected by rainfall in ENSO phases during 1950–2001 in Kurnool; **b** intercrop pigeonpea yield as affected by rainfall in ENSO phases during 1950–2001 in Kurnool



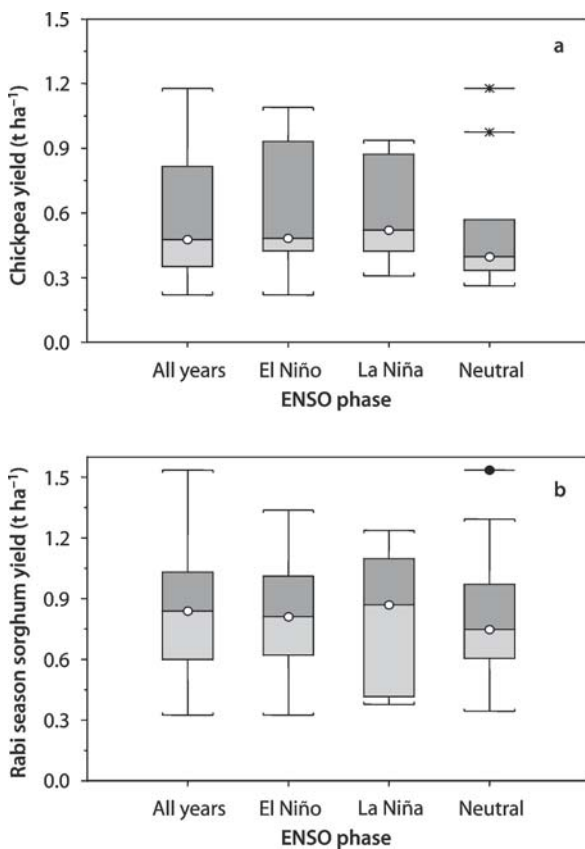
For Anantapur, ENSO phase wise crop yield analysis indicates that peanut/pigeonpea intercrop system (Fig. 17.12ab) additive performance would be higher in La Niña years ($>0.9 \text{ t ha}^{-1}$), but in neutral and El Niño years its median yields are low ($<0.7 \text{ t ha}^{-1}$) and remain below district mean yields (Fig. 17.12).

17.7.3

Farmers' Decision Options

Discussions with farmers of Kurnool and Anantapur were initiated with rapid appraisal survey jointly conducted by us in collaboration with the Regional Agriculture Research Station (RARS) scientists. These discussions with farmers were mainly aimed at understanding their perceptions on climate variability, seasonal rainfall dependent cropping management options, and availability and use of rainfall forecast information. Summary of key decisions which some of the farmers proposed to take based on the forecast information are listed in Table 17.2.

Fig. 17.11. a Chickpea yield as affected by rainfall in ENSO phases during 1950–2001 in Kurnool; **b** post-rainy sorghum as affected by rainfall in ENSO phases during 1950–2001 in Kurnool



17.7.4

Simulations of Cropping Systems

APSIM (Mc Cown et al. 1996), a cropping systems simulator capable of simulating several crops and cropping systems grown as sequential and intercrop systems in the project region, as well as “what if” management scenario analyses was used in this study. Daily-observed weather data from 1963 to 1998 for Anantapur, and from 1984 to 1998 for Nandyala were used for simulation input. Data sets available from experiments at RARS Nandyala, and ARS, Anantapur were used for cultivar parameterization to simulate crops. Cropping systems scenarios were simulated using observed daily weather data for all years as well as ENSO phase based analog years (Table 17.1) daily data to compare probable production estimates and the value of ENSO based seasonal forecasts was estimated to assess risks of loss/gain associated with cropping system in different phases. We could not use any optimization algorithm except arriving at the maximum mean of crop yield.

Fig. 17.12. a Peanut yield in intercrop as affected by rainfall in ENSO phases during 1950–2001 in Anantapur; **b** intercrop pigeonpea yield as affected by rainfall in ENSO phases during 1950–2001 in Anantapur

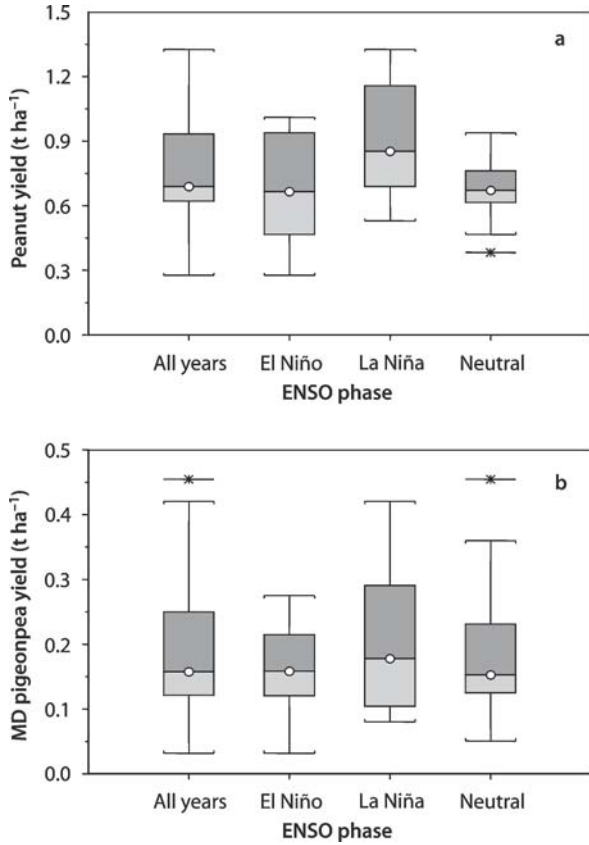


Table 17.2. Key issues in forecast that may lead farmers’ decision options in Anantapur and Kurnool as against traditional/risk-averse decision cropping systems

Location/Forecast issue	Forecast based decision options	Traditionally risk averse/ low input decisions
Anantapur		
July rainfall	Peanut/pigeonpea intercrop	Sole peanut
Late/August rainfall	Peanut/short duration pigeonpea intercrop	Sole peanut, SD pigeonpea, sorghum, horse gram
Kurnool		
June rainfall and good seasonal rainfall	Mungari cotton, intercrops like peanut/pigeonpea, sunflower/pigeonpea, and sunflower + chickpea sequence	Mungbean + chickpea, foxtail millet/pigeonpea, mungbean + sorghum
Late rainfall	Late sunflower, late sorghum	Wait for September rains
September–October rainfall	Sole sunflower, sole chickpea	Sole rabi sorghum

Cropping systems scenarios include yield estimates of traditional practice of single crop systems for all seasons and optimized ENSO phase forecast based crop production estimates. Conceptualization of these system scenarios is based on the farmers' survey results as preferred and adoptable decision depending on seasonal forecast and soil conditions (Table 17.2) for Kurnool and Anantapur.

17.7.5

Simulation Scenarios of Baseline Management

We could simulate yield estimate of rainy season sorghum and sequential chickpea system in hindcast for all years as well as ENSO phase forecast considering analog years, with sowing opportunity triggered between 15 and 25 June, when 5 days accumulated rainfall exceeded 60 mm or extractable soil water was greater than 65 mm in the wet sowing zone of the soil for Kurnool region. Farmers usually apply two bags of fertilizer per acre in different N-P-K grades (18-46-0, 20-20-0, 17-17-17, 28-28-0), giving a nutrient application (kg ha^{-1}) ranging from 42.5–70 N, 42.5–115 P_2O_5 and 42.5 K_2O . However, in simulations, we considered application of 80 kg N ha^{-1} during La Niña and 40 kg N ha^{-1} during El Niño and ENSO neutral for both the crop seasons as the optimal practice compared to baseline simulation of single crop kharif sorghum with 40 kg N ha^{-1} application for all year.

In Anantapur, a sole crop peanut is traditionally grown by risk-averse farmers which is sown any time, but mostly from the 3rd week of July to 2nd week of August, with a fertilizer application at 20 kg N ha^{-1} and this was considered as a baseline management simulation. We simulated peanut/medium duration pigeonpea cropping system with sowing triggered between 25 June and 21 July, and planting at a wide row ratio of 7:1 as the optimal management during the La Niña seasons. Peanut/medium duration pigeonpea intercrop was generally recommended for farmers to suit longer cropping season, and ICRISAT promoted peanut/short duration pigeonpea intercrop system as suitable for short seasons after carrying out systems analysis for Anantapur. During El Niño and ENSO neutral years, sowing opportunities were triggered between 15 July and 15 August with peanut/short duration pigeonpea intercrop system, at 3:1 to 7:1 row ratios under Anantapur conditions. Simulations were carried out with these intercrop systems using 40 kg N ha^{-1} application using observed weather for the ENSO phase analog years.

17.7.6

Value of Seasonal Forecasting Skill

The value of ENSO phase forecasting skill for crop management options was calculated for each ENSO phase with appropriate cropping system and management options. The potential value of optimal use of ENSO phase forecast is evaluated as the mean difference between the returns for optimal cropping system management for each ENSO phase in the time series and returns to all weather optimal cropping system management (Hansen et al. 2001). Inputs like seed and fertilizer cost, crop output prices and fixed costs are considered at the rates prevailing during March 2003, the end of crop season. Results are shown in Tables 17.3 and 17.4.

Table 17.3. Estimated crop yields and value of ENSO phase information for peanut/pigeonpea intercrop system management as compared to all weather optimal sole peanut during 1963–1998 in Anantapur region

ENSO phase	No. of years	Cropping system	Yield by ENSO phase			Value (Rs ha ⁻¹)
			Peanut (t ha ⁻¹)	Pigeonpea (t ha ⁻¹)	Net (Rs ha ⁻¹)	
El Niño	13	Peanut/SD pigeonpea	0.65	0.21	12 000	584
La Niña	11	Peanut/ MD pigeonpea	1.22	0.22	19 040	7 824
Neutral	12	Peanut/SD pigeonpea	0.830	0.35	17 080	5 664
All years	36	Sole peanut	0.868	–	10 416	–

Table 17.4. Estimated crop yields and value of ENSO phase information for sorghum + chickpea crop management as compared to all weather optimal sole chickpea during 1963–1998 in Kurnool region

ENSO phase	No. of years	Cropping system	Yield by ENSO phase			Value (Rs ha ⁻¹)
			Sorghum (t ha ⁻¹)	Chickpea (t ha ⁻¹)	Net (Rs ha ⁻¹)	
El Niño	13	Rainy season sorghum with rabi chickpea	0.67	0.94	12 000	160
La Niña	11	Rainy season sorghum with rabi chickpea	1.2	1.0	19 040	5 600
Neutral	12	Rainy season sorghum with rabi chickpea	1.1	0.6	17 080	(–3 200)
All years	36	Sole chickpea	–	1.2	10 416	–

17.8 Results and Discussion

ENSO phases have a considerable influence on the seasonal rainfall of Kurnool and Anantapur districts in the scarce rainfall zone of Andhra Pradesh, India. All La Niña phases produced higher rainfall than normal rainfall in both districts in the ensuing monsoon season, and lower rainfall during following monsoon season in all El Niño phases in both districts but for two years in Kurnool (Fig. 17.5a.). Historical crop yields of rainy season sorghum, peanut/pigeonpea intercrops were positively affected by the La Niña phase seasons, indicating that good rainfall distribution leads to higher yields in 50% of the years. Sorghum yield in neutral years is also higher compared to El Niño

years (Fig. 17.8). Hence sorghum can be a rainy season crop option except in El Niño years. Contrary to expectations, mungari cotton yielded better in El Niño years compared to neutral or La Niña years. Cotton is a deep rooted and long duration crop with standing moisture stress and solar radiation may be the factor favoring in El Niño phases, and it can be a suitable crop option in El Niño years (Fig. 17.9). Peanut and pigeonpea intercrop system is an obvious choice in the light soil areas of Kurnool and Anantapur during the La Niña phase as the median yield for both the crops is conspicuously higher and the yield increase in this phase was $>250 \text{ kg ha}^{-1}$ (Figs. 17.10 and 17.12). While chickpea yields were higher in El Niño years, its performance in La Niña was also consistently better than in neutral years (Fig. 17.11a). For Anantapur, ENSO phase wise crop yield analysis indicates that the additive performance of peanut/pigeonpea intercrop system (Fig. 17.12ab) would be higher in La Niña years ($>0.9 \text{ t ha}^{-1}$), but low ($<0.7 \text{ t ha}^{-1}$) during neutral and El Niño years (Fig. 17.12). Value of ENSO phase forecasting skill (Tables 17.3 and 17.4) has been higher in La Niña phase in both districts at Rs 7 564 for peanut median duration pigeonpea in Anantapur and Rs 5 600 for sorghum + chickpea sequential systems in Kurnool. During the El Niño phase, forecasting has the lowest value since optimal crop management with low input applications resulted in low yields as it was limited by moisture availability.

17.9

Conclusions

Through the identification of the relationship between ENSO phase based on extended reconstructed SSTs and seasonal observed weather for a small and agriculturally homogeneous region, the utility of climate forecasts in agricultural decision-making options has been established for a scarce rainfall region in Andhra Pradesh, India. Since ENSO phase analyses is the simplest method for identifying the forecast skill for the region, we used this study as a preliminary approach to sensitize farmers for seasonal climate forecast based crop management options evaluation. However the optimal crop management options presented in the study are limited and several other cropping options need to be explored.

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Application of Climate Prediction for Rice Production in the Mekong River Delta (Vietnam)

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18.1

Introduction

The Mekong River Delta (MRD) is the largest rice producing area and one of the most densely populated areas of Vietnam. However, farming is very risky because it is climate dependant. The variation of climate from year to year leads to a considerable variability in crop production. Water deficiency and water excess associated with seasonal climate variability have a significant consequence on rice production.

To secure food production in the region, it is therefore necessary to assist the farming system with seasonal climate information available from various sources. Preliminary research findings showed that there is a significant influence of ENSO phenomena on climate parameters in Vietnam (Nguyen and Ngo 2002). Bearing this in mind, this pilot study was undertaken with the following objectives: (1) to examine the relationship between ENSO indices and rainfall and temperature in the MRD, (2) to set up a demonstrative climate forecast communication to commune levels, (3) to use crop simulation to assist decision-makers.

Case studies in Long An province were conducted for the dissemination of climate forecasts and rice crop simulation. Long An province is located in the MRD, with the growing area of about 482 000 ha, of which more than 433 000 ha are under rice paddies. The main agricultural crops include rice (the main crop), sugarcane and peanut, which are secondary crops in the rice-based cropping system. The strong dependence of agriculture on the weather creates a large variability in crop yields. Also, climate variation can bring about a significant change in cropping patterns. Depending on water availability, there can be up to 2 to 3 rice crops annually. Significant parts of the province are in marginally low land, which can be affected by saline water from the sea in March–April (the dry season) and by flood in September–October (the rainy season). It is very important to have reliable seasonal forecasting in order to help farmers arrange the cropping patterns and timing so that they can make the full use of early rains and avoid early flooding.

Two communes of Long An province were selected as each is affected by a specific climate related condition. These are Thanh Phu commune of Ben Luc district, which represents salinity affected areas in the early stage of the rainy season (May–June) and Tan Lap commune of Tan Thanh district, which is affected by annual flooding during high water season (September–November).

18.2 Data and Methodology

For studying the effects of ENSO, data on monthly rainfall and temperature were collected from 18 meteorological stations in the Mekong River Delta (Fig. 18.1). ENSO indices including SSTA Niño 3+4 region and *SOI* were downloaded from the website of the Climate Prediction Center (CPC) of NOAA.

Climate forecasts were prepared and disseminated to 52 farmers of the two selected communes and to 20 officials and extension workers of Long An province during April to October 2003, prior to the onset of the rainy season, until the end of the summer-autumn crop season. The forecasts consisted of both climate information and hydrologic conditions as required by users.

Two field surveys were carried out to identify the specific needs on climate forecast information, and to evaluate the use and effectiveness of the forecasts.

DSSAT v3.5 software (Hoogenboom et al. 1999) was used for rice crop simulation for the selected sites in Long An province (Ben Luc and Tan Thanh districts). The following inputs were made for the model simulation.

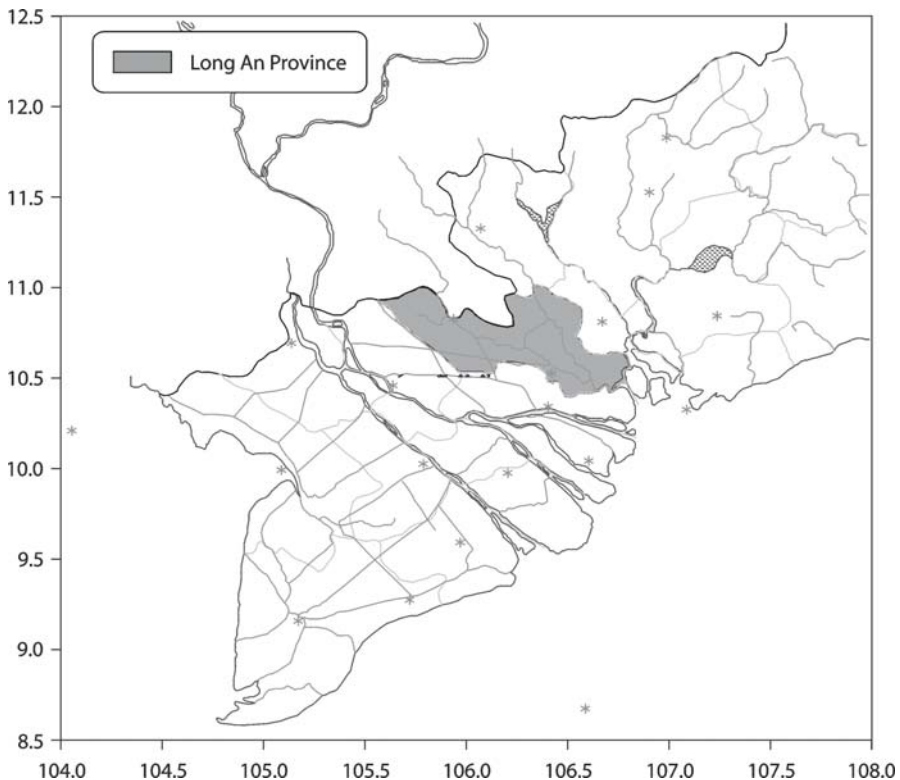


Fig. 18.1. Meteorological stations in the MRD (stars) and Long An province (dark shaded)

18.2.1

Weather Data

Daily rainfall, maximum temperature, minimum temperatures and sunshine duration data were obtained from two meteorological stations in the selected districts (Moc Hoa station in Tan Thanh district and Tan An station in Ben Luc district), for the period of 1978–2003. As the model requires solar radiation data for input files, the observed sunshine duration data were converted into solar radiation values using WeatherMan software provided in the package of DSSAT v3.5.

18.2.2

Crop Data

The rice crop varieties used in the study were VND 95-20 (at Tan Thanh district) with growing season length of 90–95 days and IR-64 (at Ben Luc district) with growing season length of 95–100 days. Both are short growing duration varieties. The crop management practices were those adapted in the field with fertilizer amounts, water depths and different planting dates.

18.2.3

Soil Data

The predominant type of soil in Tan Thanh district is gray acid sulfate soil with clay and sandy sub soils, having a depth of 140 cm. The predominant soil in Ben Luc district is slightly saline alluvial soil having a depth of 160 cm.

18.3

Results

18.3.1

Relationship between ENSO Indices and Temperature and Rainfall

The analysis has shown the impacts of ENSO on rainfall and temperature in the MRD. These effects are different depending on calendar months. The highest correlation coefficients are in the range of 0.5–0.7 between ENSO indices and temperature during March through to June. For rainfall, the correlation coefficients are lower than those of temperature. The highest correlation coefficients are in the range of 0.4–0.6 between ENSO indices and rainfall during March through May (Fig. 18.2). The lag time of 2–3 months for temperature and of 4–5 months for rainfall gives the highest correlation coefficients.

18.3.2

Field Surveys

The results of the first survey showed the need for weather and climate forecasting mainly at critical points of the rice growing seasons: the onset of the rainy season, the occurrence of dry spells during the rainy season, the salinity conditions at the end of

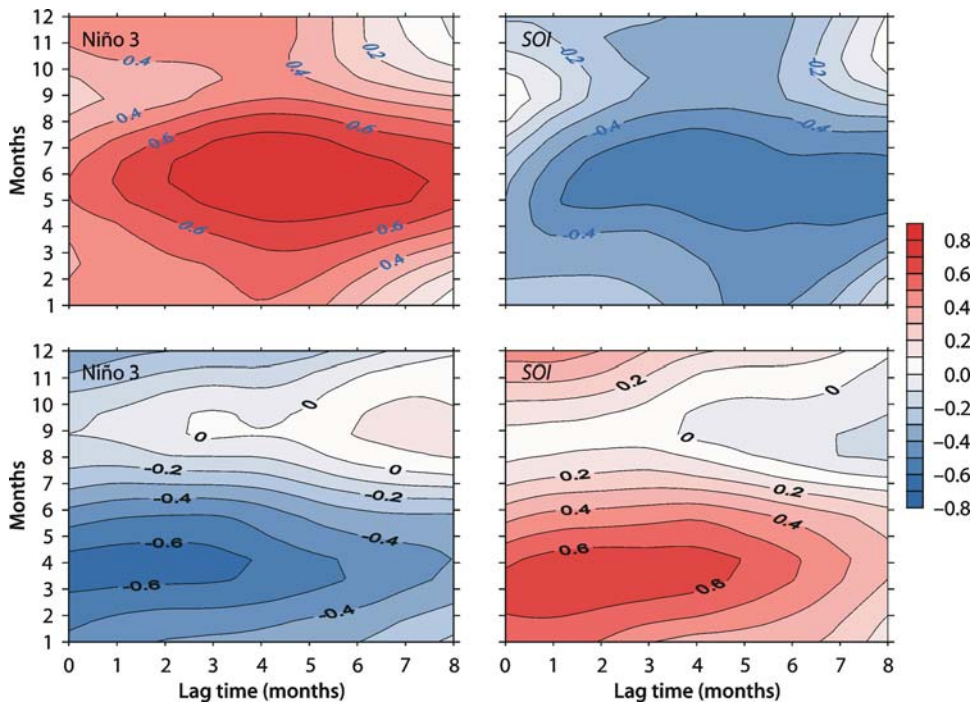


Fig. 18.2. Correlation coefficients between Niño 3.4 SSTA (*left*) and SOI (*right*) with temperature (*above*) and rainfall (*below*), averaged for the MRD. *Y-axis* denotes calendar months from January (1) through December (12), *x-axis* denotes lag time in month

the dry season and beginning of the rainy season and flood and inundation events. The lead-time required is one and three months in supplementation to the existing 10-day outlooks issued regularly by the Southern Regional HydroMet Center, SRHMC (located in Ho Chi Minh City). In addition, farmers expressed their desire to have the forecast of hydrological conditions in the forecasting bulletins. This is quite common here as their agricultural practices are affected very much by flow regime. The findings from the survey helped design suitable hydrometeorological forecasts, which include both climate outlook (for 1 month and 3 months) and hydrological conditions forecasts (for water level and salinity of several stations in the areas).

The results of the second survey showed that the climate forecasts based upon the results of the first survey were extremely useful for both farmers and agricultural workers. Farmers used the rainfall forecasts for defining the sowing dates and the harvest time. The three-month forecasts are very important for extension workers in guiding and defining farming schedules for local areas. The forecasts were used in farming arrangement, including time for sowing, fertilizer spraying, irrigation and selection of storage methods.

18.3.3

Forecast Information for Dissemination to Farmers

The communication between the forecasting centers and end users is shown in Fig. 18.3.

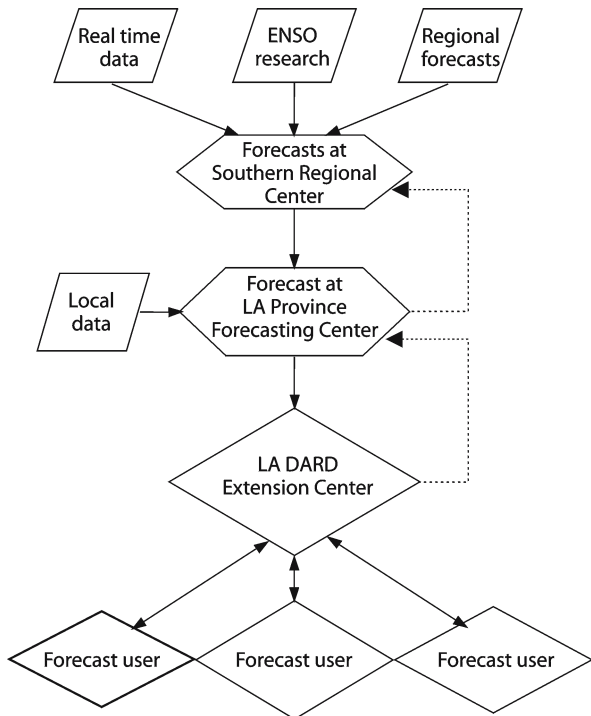
The forecasts were firstly made at the Regional Forecasting Center (RFC) located in Ho Chi Minh City. Then forecasts were sent to Long An Provincial Forecasting Center (LA PFC). The latter was responsible to finalize the bulletin and distribute the forecasts to related agencies and farmers in the province after adjusting the forecasts based on local conditions and requirements. This is the first time probabilistic forecasts were introduced to farmers. The possibilities and limitations of the seasonal forecasts were explained during meetings; however it was indicated that the users would prefer deterministic forecasts.

18.3.4

Crop Simulation

CERES-Rice model of DSSAT v3.5 software was used to simulate crop yield in Ben Luc and Tan Thanh districts (Long An province). In practice, different planting dates are applied at the locations, so the simulation was adjusted to reflect those planting dates.

Fig. 18.3. Communication of forecasts between forecasting centers and users



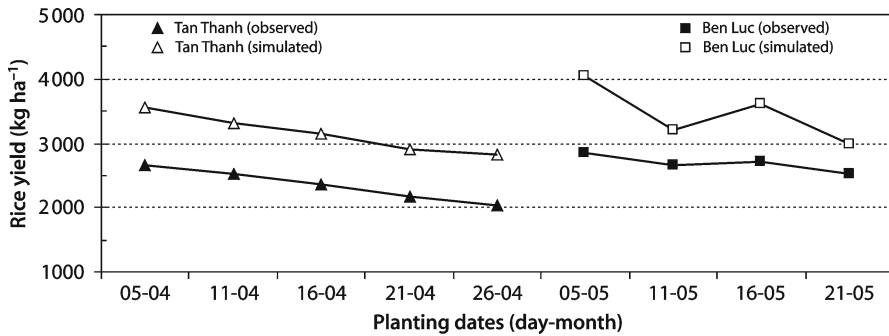


Fig. 18.4. Simulated yields vs. observed yields at different planting dates. The simulation was made with the actual weather data and crop inputs of the summer-autumn rice crop in 2003

The simulation results allowed us to define the optimum planting dates for the selected locations. For Tan Thanh district, the optimum planting date is around the first 10 days of April. For Ben Luc district, the optimum planting date is the first 10 days of May (Fig. 18.4). If planting occurred earlier or later than these planting dates, there is a possibility that a considerable decrease of the yield due to the water situation (shortage at the beginning or inundation at the end of growing period) may result.

The implementation of the project has established close cooperation between climate researchers, hydrometeorological operational forecasters in the regional and provincial levels, agricultural staff from Long An Department of Agriculture and Rural Development and staff from Long An Agricultural Extension Center. The project activities relating to rice production in the areas have received an enthusiastic involvement of local people (extension workers and farmers of Long An province).

18.4

Conclusions

Although the project has made some achievements, there are still some aspects that need to be considered and improved. They are as follows:

- The forecast accuracy, especially in the longer term needs to be improved. It is suggested that further studies on the relationship between ENSO phenomena and climate variables over the Mekong River Delta be undertaken in more detail so that the findings can be used to assist operational forecasting work.
- Improve forecast-distribution procedures of operational agencies to provide the best possible benefits of climate information for users.

In order to exploit the full benefits of the research results it is proposed to conduct a study on the effects of ENSO and climate change on water resources and the coastal zone of the Mekong River Delta.

Acknowledgements

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Climate Prediction and Agriculture: What Is Different about Sudano-Sahelian West Africa?

P. C. S. Traoré · M. Kouressy · M. Vaksman · R. Tabo · I. Maikano · S. B. Traoré · P. Cooper

19.1

Introduction

Recurrent drought conditions that prevailed in the Sahel region of West Africa during the 1970s and 1980s have seriously challenged the resiliency of ecosystems and the adaptive capacity of human societies (IPCC 2001). This has triggered increased attention from the scientific community, resulting in a significant augmentation in climate-related publications and allowing for a better understanding of the complex regional and local climates.

Of prime importance is an improved appraisal of the variable nature of rainfall. When Hulme (2001) states that there is no such thing as ‘normal’ (mean) rainfall in the Sahel, he alludes to one of the most fundamental characteristics of the West African climate: its ‘normality’ is to be variable over a range of timescales. We first review the causes of this unique variability, then discuss its implications in terms of the prerequisites for beneficial use of forecasts (Hansen 2002), and the way forward in Sudano-Sahelian smallholder agriculture. Emphasis is put on the legacy of varietal adaptation as a powerful strategy for managing the stochasticity in climate – and further exploiting it in improved breeding programs, in parallel with rejuvenated early agrometeorological crop yield assessments.

19.2

The Context: Distinctive Climate Variability

19.2.1

A Variety of Forcings

A unique combination of external and internal forcings makes West Africa one of the most climatically sensitive regions of the world (Zeng 2003), and probably one of the most challenging to decipher, interpret and model (Jenkins et al. 2002) due to the superposition of numerous competing variability modes. Variability in rainfall results from location and astronomic forcings, which determine the seasonality of climate; oceanic-atmospheric large-scale forcings, which condition regional circulation and determine the season’s potential; synoptic and sub-synoptic features, which control actual weather patterns and determine the realization of the season (Lister and Palutikof 2001). Interactions between these determinants are further complicated by land surface conditions which act as ‘after-burners’ of the regional climate engine (Traoré 2004).

19.2.1.1

Ocean and SST Forcings

There is still controversy over how SST and coupled ocean-atmosphere phenomena affect West Africa's climate. ENSO is known to influence the global summer monsoon system from China to West Africa through the Walker and Hadley circulations (Quan et al. 2003), but teleconnections with West African rainfall are less clear cut than for other regions of Africa (Nicholson and Kim 1997). More research on the modulating role of Atlantic SST variability (Camberlin et al. 2001; Janicot and Harzallah 1998) could help address the lack of consensus over ENSO's influence, drawn from apparent contradictory findings obtained over different timescales (Rowell 2001; Mason and Goddard 2001). There is growing agreement that Sahelian drought is not associated with a unique SST anomaly pattern, and that it results from the combined influences of the global SST anomaly field and interconnected individual oceanic contribution patterns (Folland et al. 1986; Giannini et al. 2003).

19.2.1.2

Synoptic Features

Similarly, current understanding of African convection remains deficient (CLIVAR 1999). African Easterly Waves (Cook 1999) provide a sound framework to explain the formation of squall lines and mesoscale convective systems through convective feedback loops on meteorological medium-range timescales (Landsea et al. 1999). They appear to be the key mechanism behind precipitation patterns during the core of the rainy season (Gu and Adler 2004) where the number of individual events explains most of rainfall variability (D'Amato and Lebel 1998; Le Barbé and Lebel 1997), but account for only a proportion of seasonal rainfall on the ground (Taleb and Druyan 2003). Further investigations are needed to understand processes that link synoptic events to regional and global circulation (e.g. MJO, Matthews 2004), tropospheric jets (Nicholson and Grist 2003), and land surface conditions (Fontaine and Philippon 2000).

19.2.1.3

Land Surface Forcings

It has long been suggested that degraded vegetation cover would result in decreased evapotranspiration, reduced precipitation and eventually further degraded cover, initiating an albedo-precipitation feedback cycle (Charney 1975). The lagged response of vegetation cover and soil moisture, which amplify low-frequency oceanic forcings (Giannini et al. 2003; Ward 1998) and buffer out high-frequency 'noise' appear required to closely simulate rainfall variations (Zeng et al. 1999). This conclusion should be no surprise owing to the unrivalled tropical landmass of northern Africa, but the transition from research on land-atmosphere modeling (Goutorbe et al. 1997; Dolman et al. 1997), causative mechanisms of climate change (Long and Entekhabi 2000; Xue et al. 2004) onto the operational implementation of dynamics land surface schemes in climate models remains incomplete in spite of the rapidly growing array of remote sensing observations.

19.2.2

The Problem: A Notoriously Unpredictable Growing Season

19.2.2.1

From Rainfall Variability to Predictability: The Skill Issue

Meanwhile, regional climate prediction skill at various time scales remains modest (IPCC 2001). Contrasting SRES ensemble simulations for seasonal rainfall over Southern Africa (forecasting a likely decrease) and the West African hinterland (poorly specified forecast) further suggest that variability and predictability do not necessarily go hand in hand. Models' knowledge base originally tuned to maximize performance over the Pacific region on interannual timescales (CLIVAR 1999) and relying on a subset of mostly oceanic and atmospheric predictors works satisfactorily when ENSO wields a dominant control over regional climate (even when interannual variability is highest: Southern Africa) but fails when the distribution of forcings is widespread (e.g. West Africa). Sometimes simple statistical methods outperform dynamical models constrained by poor initialization of regional soil moisture and lack of dynamically prescribed vegetation (Garric et al. 2002). Low local skill levels dominate in spite of an understandable urge to demonstrate the value of seasonal forecasts through more attractive scores at the aggregate level. For example, 'high degrees of skill' for the JAS period (IRI 2005) should be carefully interpreted in terms of scale-compatible applications (such as large watershed management), because any space-time downscaling will irremediably result in a loss of skill as suggested by Gong et al. (2003). The inability of dynamic models to correctly reproduce the succession of sub-grid scale convective events severely limits their applicability in hydrology (Lebel et al. 2000) and even more so in smallholder agriculture.

19.2.2.2

From Climate to Agriculture: Limited Predictand Relevance

The scale mismatch issue becomes more challenging indeed when agricultural applications are at stake. In Sudano-Sahelian West Africa, proper understanding of intra-seasonal variability patterns is of critical importance because of the highly unstable onset of the rainy season and the frequency of dry spells (Ati et al. 2002; Dodd and Jolliffe 2001; Omotosho et al. 2000; Ward et al. 1999). The length of the growing period (LGP) is mainly a function of the date of the first rains (Sivakumar 1988), which is delayed with latitude and varies widely from year to year (Fig. 19.1a). This important relationship basically results from the independence between the onset and end dates of the rainy season (Fig. 19.1bc). The ability to predict seasonal rainfall is then relatively less important, with the exception of the northernmost desert margins, where LGP is 'invariably' very short and water availability – as opposed to water distribution – becomes the central issue (Ingram et al. 2002). In that marginal agricultural environment running from southern Mauritania to northern Burkina Faso, southern Niger and central Chad, there might be scope for the application of selected seasonal forecasts (e.g. JAS rainfall), for which reasonable skill is observed with short lead times (Neil Ward, IRI, New York, personal communication). However southwards across Sahelian, Sudanian and northern Guinean agro-ecologies, the relationship between

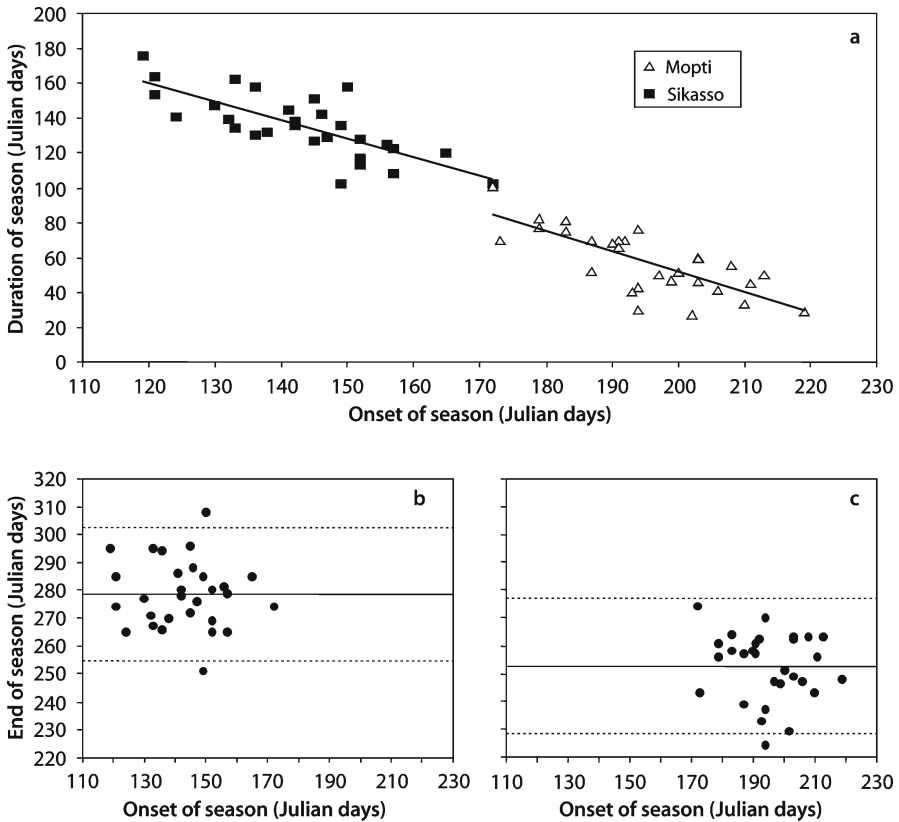


Fig. 19.1. **a** Duration of rainy season as a function of onset date in Julian days for Sikasso (northern Guinea zone, $11^{\circ}21' N$) and Mopti (Sahelian zone, $14^{\circ}31' N$); normal period: 1971–2000; **b** relationship between onset and end dates for Sikasso; average end date is highlighted by *continuous line* with ± 2 standard deviations (*dashed lines*); average end: 6 October, standard deviation: 12.0 days; average onset: 23 May, standard deviation: 12.9 days; **c** relationship between onset and end dates for Mopti; average end date is highlighted by *continuous line* with ± 2 standard deviations (*dashed lines*); average end: 10 September, standard deviation: 12.2 days; average onset: 15 July, standard deviation: 11.9 days

3-monthly rainfall, soil water regimes and plant growth patterns is less clear cut: the relevance of seasonal products for agricultural applications therefore decreases.

19.2.2.3

Prospects for Temporal Downscaling: Disciplinary Divergences

Important ongoing work in the framework of the Multidisciplinary Analysis of the African Monsoon project (AMMA 2005) indicates that any potential application of downscaled seasonal forecasts will need to overcome a persistent dichotomy between climatologists and agriculturalists when it comes to farm decision-making advisories. The former advocate later sowing dates synchronous with an abrupt northward shift of the ICTZ, which they connect to monsoon onset, as opposed to the pre-onset (Sul-

tan and Janicot 2003). The latter insist that the risk linked to delayed sowing (N leaching, lower radiation and temperatures, rainfall aggressivity on younger shoots, waterlogging, pest pressure and mostly competition from weeds) is considerably larger than the risk, associated with farmer earlier planting strategies, of losing 2–3 kg ha⁻¹ of seeds (Vaksmann et al. 2005). Many of the biotic and abiotic stresses that impact final yield are not taken into account by water balance models (Sultan et al. 2005) and could explain these divergent views of what could be a safe ‘agronomic’ start to the cropping season.

19.2.3

What are the Options in the Face of Climate Variability?

19.2.3.1

Applicability of Response Farming

“Response farming springs from research on rainfall behavior and its predictability in a ‘cropping systems design’ project in Kenya [...]” (Stewart 1988). In and of itself, this introductory sentence summarizes the tight association between climate forecasting (rainfall predictability) and “opportunity cropping” tactics (ibid.) promoted by response farming (RF). The fact that RF originated in a region characterized by a vulnerable population associated with a high rainfall variability and a fair level of ENSO-based predictability (Kenya) is likely not a product of chance and has probably contributed to a worldwide success story of pilot applications of seasonal climate forecasting in agriculture with Kenya (and notably the Machakos District) a popular benchmark area throughout the years (Rao and Okwach 2005; Hansen and Indeje 2004). In any case, the potential usefulness of seasonal forecasting should be embedded in a down-to-earth assessment of current practices and possibilities. In the Sudano-Sahelian region, considering such options as shifting crop mixes and response farming tends to assume far-fetched levels of farmer flexibility in a socio-economic context still marked by risk-adverse, conservative practices, and might thus be unrealistic (Abou Berthé, personal communication). This is not to say that vulnerability deprives farmers of responsiveness, rather that they will deliberately take the risk to respond to those signals that are unequivocal, and likely ignore those which are uncertain. This dichotomy was demonstrated in year 2000, when an unequivocal decrease in purchase prices by the cotton parastatal prompted a nationwide farmer strike with widespread changes in crop mixes in southern Mali. While illustrating clear independence from political power by non-subsidized farmers (contrary to developed countries), this does not imply that the same cotton farmers would be willing to risk their food security by responding to a seasonal forecast which, contrastingly, is largely uncertain.

Traditional climate risk management practices by Sudano-Sahelian farmers include direct sowing, low planting densities, distribution of early and late maturing types throughout the landscape and spreading sowing dates (Ouattara et al. 1998). Potential innovations include contour ridge tillage cultivation, cover plants and mulching, zaï. Several of these have the potential to concurrently reduce climate risk and increase productivity (De Rouw 2004) in a ‘conventional’ response farming framework, provided reliable climate information is available. A large component of farmers management strategies however resides out of the response farming realm as it relates to specific adaptation traits engraved inside plant genetic resources.

19.2.3.2

Legacy from the Field: Plant Traits Encapsulate Variability Management

Traditional handling of plant genetic resources condenses most aspects of adaptation to climatic variability in subsistence agriculture and is known to contribute fundamentally to the development of sound production systems (WMO 2003). It is today slated for intense, conflicting questioning at the nexus of agricultural intensification processes, intervention policies and advances in biotechnology – before development and growth of agricultural income allow for a wider spectrum of response farming options. In continental West Africa, photoperiod (PP) sensitivity is required to best fit crop cycle to the probable duration of the season and is one example of the critical ingredients of environmental adaptation. It allows for grouped flowering at the end of the rainy season for a wide range of planting dates (Traoré et al. 2000) and is present in staple cereals (Mahalakshmi and Bidinger 1985) and other crops (Brink et al. 2000) with some of the highest recorded sensitivity levels worldwide. It helps minimize grain mold, insect and bird damage that affect early maturing varieties, and avoid incomplete grain filling, a problem for late maturing varieties faced with water shortage at the end of season (Cochemé and Franquin 1967; Curtis 1968; Kassam and Andrews 1975). Tillering is yet another example of unique adaptation trait, controlling the partitioning of biomass across plant organs.

It is tempting to make a parallel between contrasting levels of climate predictability and apparently marked differences in PP sensitivities observed between crops of West Africa and Southern Africa. It could be hypothesized that higher predictability of the length of growing period (LGP) in Southern Africa would favor the selection of a number of fixed maturity groups, best suited to the expected duration of the cropping season. Conversely, uncertainty associated with LGP in continental West Africa would logically tend to eliminate PP-insensitive material. Further investigation will show whether landrace PP sensitivity can be trusted as a good indicator of climate unpredictability.

19.3

Forecasts for Smallholder Food Security: Which Way Forward?

19.3.1

Where Do We Stand Now?

A few exploratory studies have confirmed Sudano-Sahelian farmers' expected interest in climate forecasts, and the determinants of potential response strategies (Ingram et al. 2002; Roncoli et al. 2004). Conclusions substantiate farmers' understanding of uncertainty, risk and opportunities associated with the use of predictions, but also highlight the inadequacy of forecasts which (regardless of skill) do not fulfill their need for estimates of season onset and end dates, time distribution and total amount of rainfall (in decreasing order of priority). Interestingly enough, these studies do not mention the widespread use of PP-sensitive cereals as one central, ingenious and sophisticated strategy to ensure food security even in the most erratic of seasons (National Research Council 1996), and how that practice would interact (or interfere) with the prospective use of seasonal forecasts. This contrasts with the increasing number

of promising applications elsewhere, even though most successful cases are confined to regions facing open oceans and displaying high predictability levels such as Australia, Argentina, Florida, Kenya or Southern Africa (Hammer et al. 2001). The difficult challenges of seasonal predictability and agricultural resilience in Sudano-Sahelian West Africa might also explain the local dominance of health-related applications in the Africa Regional Program implemented by IRI and its partners.

19.3.2

Develop Dynamic Land Surface Schemes in Climate Models (Long-Term)

However distant from smallholders livelihoods (and agricultural research) this priority may appear, abundant literature points to the need to improve the representation of land forcing in climate models, if higher predictability of local and regional climates is to be attained. The implementation of this consensual effort has possibly been delayed by the lack of extensive satellite time series but is quickly picking up as the climate science community now strongly acknowledges the role of 'new and/or better existing observational networks as the drivers of model improvement and thus of improved climate anomaly predictions' (Grassl 2005). Differing results by Wang et al. (2004) and Crucifix et al. (2005) on the impact of vegetation dynamics on rainfall variability ('memory' or 'after-burner' effect) provide encouraging signs that significant progress is underway, with important breakthroughs possible in the coming years.

19.3.3

Adapt Crop Models (Short-Term)

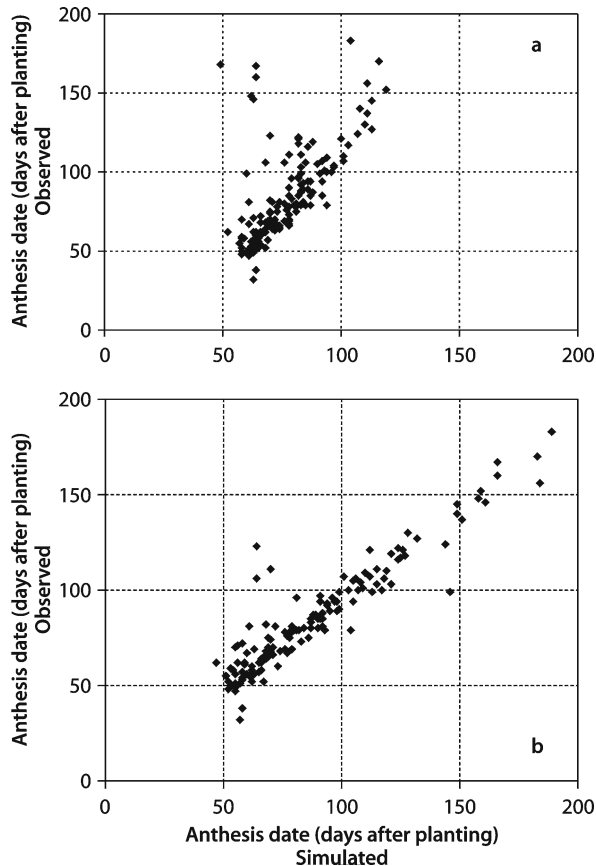
A more immediate prerequisite to the successful identification of profitable tactical management decisions based on seasonal forecasts is that crop simulation models must first be able to effectively reproduce the characteristics of local cropping systems (Phillips et al. 1998). This presents difficult challenges for a range of models available for use in West Africa, because of such peculiarities as surface crusting, low planting densities and heterogenous canopies, etc. Critical advances were however made, e.g. in the adaptation of PP response in the CERES-Sorghum and -Millet modules of the DSSAT-Century cropping systems model. In its original form, a linear photothermal response resulted in underestimates of crop cycle duration for late-maturing landraces (Fig. 19.2a). A threshold-hyperbolic function was shown to simulate cycle duration (Fig. 19.2b) for both PP-sensitive and PP-insensitive material (Folliard et al. 2004). This work allowed to revisit the popular, but incorrect photothermal approach widely used in modeling crop development (Robertson 1973). Other ongoing work seeks to improve models poor ability to simulate yield components because of flaws in the timing of stem elongation (occurring after panicle initiation in CERES) and the inadequate partitioning of assimilates resulting in inflated harvest indices for Sudano-Sahelian landraces.

19.3.4

Apply GIS and Crop Models to Target Breeding Strategies (Medium-Term)

A popular misconception argues that landrace rusticity traits related to development (e.g. photoperiod sensitivity) and growth (e.g. tillering) are incompatible with pro-

Fig. 19.2. Days to anthesis computed over a sample size of 146 from planting date experiments conducted between 1992 and 2003 in six locations (Cinzana, Koporo-Pen, Katibougou, Samanko, Sikasso, Sotuba) covering a latitudinal gradient in Mali. Participating sorghum and millet varieties: CSM219, CSM388, Jebana, M9D3, Nazongala, Sanioba-03, Sanioba-B, Surukuku, W33, Wasulu. PP response; **a** cumulative linear (CERES original), $R^2 = 0.37$, $RMSE = 25.7$; **b** threshold hyperbolic (Folliard et al. 2004), $R^2 = 0.88$, $RMSE = 11.6$



ductivity traits. This simply is not the case, and the preservation of stability is a central paradigm in breeding for productivity (Dingkuhn et al. 2005). Photoperiod sensitivity is positively correlated with productivity as it allows for longer vegetative phases, increased production of biomass (Reyniers et al. 1998) and augmentation of yield components such as seed number per panicle (Vaksman et al. 1998). Major dwarf genes can be mobilized to shorten stems and augment harvest indices in photoperiod sensitive sorghum (Kouressy et al. 1998). Tillering is compatible with high yields (Lafarge et al. 2002) and helps early stand development and rapid canopy closure to limit weed invasion and soil erosion. Figure 19.3 illustrates the potential use of models and GIS to investigate genotype \times environmental interactions in a spatially explicit manner over the CILSS region of West Africa. Here, a large amount of learning from indigenous knowledge, mechanistic crop modeling and sensitivity analyses is synthesized to map varietal adaptation based on a phenological criterion which seeks to align (as do farmers and plants) flowering dates on the end of rains – instead of relying on the misleading average (‘normal’) length of growing season (LGP). Next steps for improved targeting of breeding programs will involve higher level mapping to represent

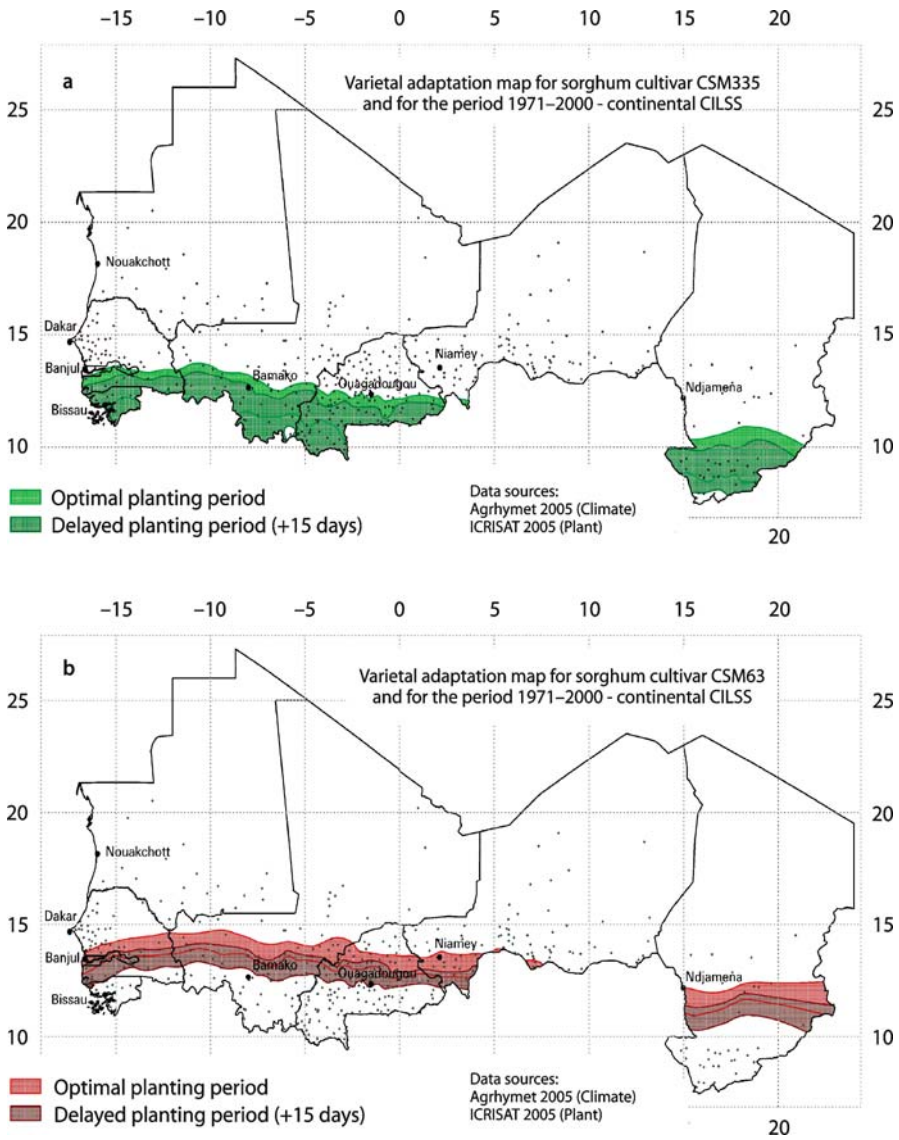


Fig. 19.3. Varietal adaptation maps for cultivars CSM335 (a) and CSM63 (b) and for the 1971–2000 period (continental CILSS countries). Here, adaptation is defined based on phenology, i.e. when the average flowering date occurs 20 (± 10) days before end of season. End of season occurs when a moving 10-day average of daily rainfall drops below the ETP line (~end of humid period, adapted from Cochemé and Franquin 1967). The two planting periods, optimal (shortly after onset of humid period) and delayed, reflect the traditional spread of sowing dates. The adaptation strip for early-maturing, non-PP sensitive CSM63 is thinner than that of late-maturing, PP-sensitive CSM335 on any given date. It rapidly migrates southwards for delayed sowing, with relatively small latitudinal overlap for a 15-day delay, in contrast to CSM335. CSM63 can be seen as a variety of large geographic adaptation if, and only if, there is a shift in sowing dates. CSM335 demonstrates both large temporal adaptation (small latitudinal shift, large overlap) and large geographic coverage. PP-insensitive germplasm (like CSM63) is more likely to benefit from improved climate forecasts, but PP-sensitive cultivars could remain very competitive

the larger spectrum of abiotic, biotic, and socio-economic constraints to varietal adaptation.

19.3.5

Revisit Early Crop Yield Assessment Techniques (Medium-Term)

The suggestion to incorporate rusticity traits in breeding strategies as a way to temporarily or durably ‘hard-code’ variability management should not be seen as a pessimistic attempt to downplay potential tactical uses of seasonal forecasts in Sudano-Sahelian agriculture or (even worse!) underrate the critical importance of agroclimatic risk analyses. Rather, we believe that before forecasting skill and smallholder endowment improve, there is room for a parallel and renewed effort in the agrometeorological early estimation of crop production. A much larger array of data sources (from climate models and remote sensing), finer understanding of crop growth and development (from process-based models) and stochastic data assimilation (DA) techniques now allow a more operational ‘invigoration’ of probabilistic agroclimatology by looking at ‘weather within climate’ (Hansen et al. 2005) in the context of facilitating investment in rainfed agriculture (Cooper et al. 2005). Predictability at intermediate intra-seasonal (~20–60 day) timescales has been somehow neglected in favor of more fashionable seasonal products, but holds promise in the short term as it will benefit from enhanced representation of continental forcings (Céron 2004) and ongoing projects such as AMMA (2005). Experimental hybrid monthly forecasts are routinely published by ECMWF since October 2004 with the objective to bridge the gap between extended weather and seasonal timescales, a priority focus area from a climate science perspective (Grassl 2005). Figure 19.4 proposes a schematic procedure to improve final model yield estimates using such in-season rainfall forecasts and bi-weekly satellite biomass observations (from ASTER) in a sequential DA framework. Sequential DA is computationally more efficient than variational DA recently tested for crop yield estimation (Guérif and Duke 2000; Bach and Mauser 2003). It can accommodate a wider range of uncertainty as Monte Carlo ensemble generation allows for any statistical form of time/space correlation in error structure (Crow and Wood 2003), and can propagate the full probabilistic climate information into yield estimates along with measurement and model uncertainties (Jones et al. 2006). It is better suited for near-real time applications oriented towards the prediction of future system states that is key to early warning systems.

19.4

Conclusions

In 2003 we started a START-funded project entitled ‘Bytes for Bites: Translating Climate Forecasts into Enhanced Food Security for the Sahel’ carried by a sense of ‘environmental urgency’ (Raynaut et al. 1997). Little did we realize then that Sudano-Sahelian farmers (and their crops) still are, in many ways, experts in resilience (Batterbury and Warren 2001; National Research Council 1996) and that our early assumption of *human vulnerability* could be challenged by generations of trusted kinship networks (Roncoli et al. 2001) and sophisticated practices including the selective management of plant genetic resources.

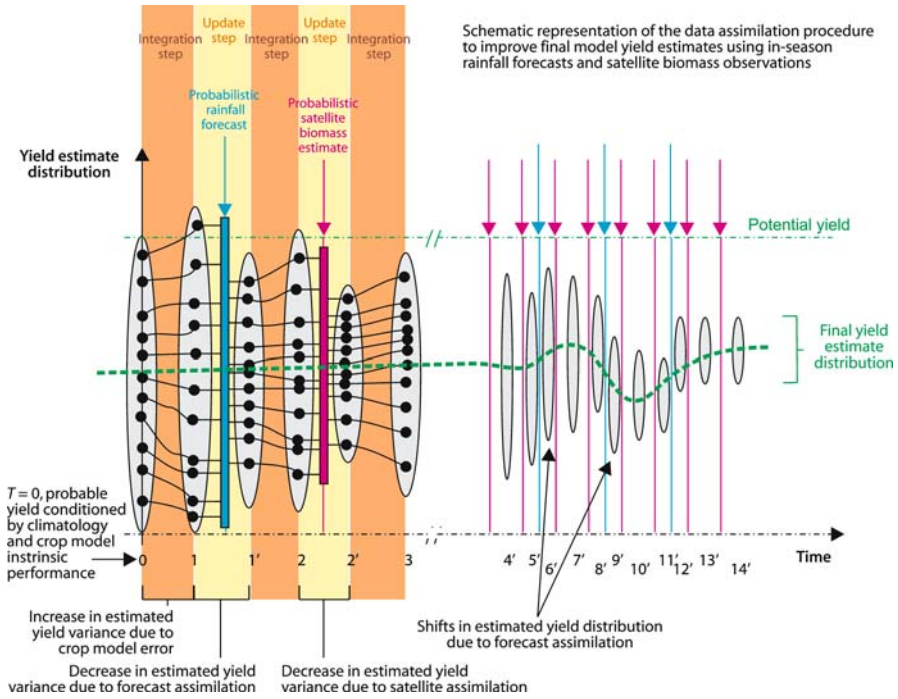


Fig. 19.4. Schematic representation of a data assimilation procedure to improve final model yield estimates using in-season rainfall forecasts and satellite biomass observations. At $T = 0$, a crop model (mechanistic or empirical) is initialized with an ensemble of equally likely conditions (using a Monte Carlo technique). The model is then propagated forward in time with each realization of the ensemble. When estimates of system states (e.g. biomass), model parameters (crop type, sowing date, ...) or boundary conditions (cumulative rainfall) become available an Ensemble Kalman Filter (EnKF) updates these and the measures of uncertainty thereof. EnKF has improved early estimates of system states in physical oceanography, meteorology, air pollution monitoring, hydrological streamflow forecasting, petroleum engineering, fish stock assessment, and more recently carbon sequestration studies (Jones et al. 2006)

A thorough review of current knowledge on regional climate revealed that in Sudano-Sahelian West Africa, *climate predictability* remains limited and very likely constrains the beneficial use of current forecasts in the region. This problematic setting combines with a context of low endowment of smallscale farmers and still deficient information systems to hamper *decision capacity* at multiple scales by reducing the array of options available to take advantage of developing seasonal forecasting opportunities.

With this, the successful application of seasonal forecasts in Sudano-Sahelian smallholder agriculture appears today premature, contrasting with several other regions of Africa and the world, some even close (Adiku and Stone 1995) with more immediate potential.

This will change over the next decade, as progress on the implementation of retro-active land-atmosphere interactions in dynamic climate models yields tolerable uncertainty levels for uptake by Sudano-Sahelian farmers, and production systems

intensify under growing population pressure, increase in sedentary agriculture and fallow reduction. Meanwhile, a range of preparatory activities can be pursued with benefits in the shorter term: the ongoing adaptation of crop models to simulate local crops and farming systems (Folliard et al. 2004), their coupling with GIS technologies to target regional breeding programs (Soumaré et al. 2005), and a 'rejuvenation' of early agrometeorological crop yield assessment techniques using the latest stochastic data assimilation approaches within the rapidly expanding spectrum of data sources (Traoré 2005). The latter offers timely prospects for the use of within-season, intermediate timescale forecasts in operational early warning systems and, possibly, selective response farming by Sudano-Sahelian smallholders. In a few years, progress achieved on these fronts will combine with improved predictability of climate variability trends to investigate agricultural impacts of global and regional change, and specifically the sustainability of existing and alternate patterns of adaptation (Sivakumar et al. 2005).

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Can ENSO Help in Agricultural Decision-Making in Ghana?

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20.1 Introduction

Rainfall variability has become a major agricultural issue in sub-Saharan Africa, especially since crop production is mainly rainfed. Irrigation technologies are expensive and their implementation is slow. Many researchers now believe that some understanding of the causes of rainfall variability would lead to measures that could be used to investigate reduction in total rainfall and/or drought effects.

There is now ample evidence that rainfall in many parts of Africa can be linked to global circulation phenomenon. Ogallo (1988) has shown that rainfall in Kenya is influenced by the Southern Oscillation Index (*SOI*). West African rainfall especially in Sahel has been known to be linked to sea surface temperature (SST) in the Pacific (Hulme et al. 1992). To be useful for agricultural decision-making, four conditions must be met: (1) sufficient correlations must exist between global circulation phenomena and local rainfall (2) evidence that indeed crop yields differ for the different ENSO phases (3) forecast period must have sufficient lead time before the cropping season commences and (4) ability to translate forecasts into management decisions (e.g. crop choice, planting date, fertilizer application, etc.).

Out of the four issues, it is only in case (1) that there is evidence of research progress in Ghana. Opoku-Ankomah and Cordrey (1994) showed a significant correlation between simultaneous Atlantic SSTs and rainfall in many parts of Ghana. With the view of forecasting seasonal rainfall, Adiku and Stone (1995), in another study, investigated the relationship between the *SOI* phase established in April and seasonal rainfall (April to July) and obtained a significant correlation for some sites located along the southern coasts of Ghana. However, April-based *SOI* does not provide sufficient lead time for effective agricultural planning.

Research efforts must now be directed towards establishing relationships between Global Circulation Indices and seasonal rainfall in Ghana having appreciable lead time of at least three months. Some studies by Adiku (2003) seem to suggest that the October-November-December (OND) SSTs in the Niño 3 Pacific region popularly referred to as ENSO may offer a possibility for seasonal rainfall forecasting in southern Ghana with an appreciable lead time.

In this study, we explore further this relationship with a view to identify zones where the forecast skills are significant. We also aim at demonstrating, using coupled climate/crop modeling, that the OND ENSO phase affects the yields of peanut and maize at some localities. Finally, we propose a working scheme to operationalize ENSO for agricultural planning.

20.2 Materials and Methods

20.2.1 Sites

Nine sites (Axim, Accra, Ada, Akatsi, Akuse, Kpandu, Kumasi, Yendi and Wa) in different climatic zones of Ghana were selected. The first five sites lie near the southern coastline of Ghana. Kpandu lies in the savanna-forest transition, Kumasi lies in the semi-deciduous tropical rain forest located in the middle belt of Ghana. Yendi and Wa lie within the interior savanna in northern Ghana. Except for Yendi and Wa where rainfall is unimodal (May to October), all the other sites experience bimodal rainfall with the major season from April to July and the minor season from September to November.

20.2.2 Data Sources and Analysis

Daily rainfall records for the various sites were obtained from the Meteorological Services Department, Accra, Ghana while the OND SSTs (1960 to 2000) were downloaded from the International Research Institute for Climate Prediction website. The rainfall years were sorted into three ENSO phases namely El Niño, La Niña and neutral years according to Japan Meteorological Agency (JMA). Rainfall records for seven out of the nine sites namely: Axim, Accra, Ada, Akuse, Kumasi, Yendi and Wa covered the period 1961 to 1990. This period involved eight La Niña and El Niño events each and fourteen neutral events; Kpandu (1964 to 1990) also involved eight La Niña and El Niño events each and eleven neutral years while Akatsi (1976 to 2000 excluding 1991) involved five La Niña, seven El Niño and twelve neutral events.

For each site the seasonal rainfall for each year was sorted according to the ENSO phase. For sites within the south of Ghana, only the major season was considered. Using Box and Whisker plots (not shown) the median rainfall was determined for each ENSO phase. Thereafter, the seasonal rainfall at each site was correlated with the OND Niño 3 SST anomalies.

20.2.2.1 *Simulation of Peanut and Maize Yields*

The CROPGRO-Peanut and DSSAT-Maize models (Boote et al. 1998) were used to simulate the long-term yields of peanut and maize at Akatsi. The peanut model was previously calibrated and validated for the coastal savanna zones by Adiku et al. (2001). The maize model was validated in 2003 using data from an ongoing study on maize-based cropping system at Kpeve located in the southeastern ecological zone of Ghana. Soil input data for the crop models were obtained for Akatsi from previous studies at Akatsi (Adiku et al. 2001). Weather input data were obtained from the Meteorological Services Department, Accra as noted above. As the data did not include solar radiation, sunshine hours were converted to solar radiation according to the Angstrom formula (FAO 1998):

$$R_s = (a_s + b_s \frac{n}{N}) R_a$$

where: R_s = solar or shortwave radiation ($\text{MJ m}^{-2} \text{d}^{-1}$); n = actual duration of sunshine (hours); N = maximum possible duration of sunshine or daylight hours (hours); n/N = relative sunshine duration; R_a = extraterrestrial radiation ($\text{MJ m}^{-2} \text{d}^{-1}$); a_s , b_s = Angstrom values; $a_s + b_s$ = fraction of extraterrestrial radiation reaching the earth on clear days.

The values of a_s and b_s were set at 0.25 and 0.50 respectively according to FAO (1988). The yields of peanut and maize were simulated for each of the 24 years at Akatsi (1976–2000) using three planting dates (PD): Julian day 73 (i.e. 14 March, as early planting date), 97 (i.e. 7 April, as intermediate planting date) and 120 (i.e. 30 April, as late planting date). At the beginning of each simulation, moisture content of the top 30 cm of the soil profile was set to field capacity. The planting density for peanut was set at 13 plants m^{-2} and that for maize was 6 plants m^{-2} . These conform to the densities commonly found in farmers' fields. For maize, nitrogen application was varied between 0 kg N ha^{-1} (control), 60 kg N ha^{-1} (recommended rate) and 120 kg N ha^{-1} (high application rate).

The simulated peanut and maize yields were sorted according to ENSO phases, ranked from smallest to the largest and the cumulative relative frequencies determined. Probability or cumulative distribution functions (CDFs) were constructed for each planting date for the various ENSO phases. Preference for a given planting date was based on the stochastic dominance concept (Anderson et al. 1977). From a pair-wise comparison of the CDFs of any two cropping strategies, the strategy whose CDF lies to the right is considered preferred (more is preferred to less). Maize yield increases with respect to increased applied nitrogen formed the basis for the choice of nitrogen fertilizer rate.

20.3 Results and Discussion

20.3.1 Rainfall Analyses

Table 20.1 shows the median rainfall for all sites according to ENSO phases as well as the correlation coefficients between rainfall and OND SST anomalies in the Niño 3 Pacific region. Out of the six sites located in the southern part of Ghana, ENSO-seasonal rainfall correlation was highly significant at two sites namely Axim and Akatsi and significant at Kpandu. At Axim there is as much as 500 mm difference between La Niña and El Niño events, 183.8 mm at Akatsi and 102.0 mm at Kpandu. The correlation coefficients at the other two southern sites of Accra and Akuse did not show a significant correlation but the La Niña-El Niño rainfall differences of 169.3 mm and 182.4 mm respectively were higher than the 102.0 mm observed for Kpandu where there was a significant correlation. This might be suggestive of an appreciable ENSO influence at most of the sites in the south of Ghana. ENSO influence appears weak in the middle belt of Ghana as shown by the data for Kumasi. The correlation coefficient of $r = -0.32$ was not significant and the observed La Niña-El Niño rainfall difference of

Table 20.1. Median seasonal rainfall (mm) and their OND SST anomaly correlation coefficients

Site	ENSO phase			Correlation coefficient
	La Niña	Neutral	El Niño	
Axim	1 429.2	1 408.4	955.2	-0.47 ^a
Accra	569.5	512.9	427.5	-0.29 (ns)
Ada	646.8	557.9	463.0	-0.27 (ns)
Akatsi	496.6	478.5	314.2	-0.56 ^a
Akuse	573.3	616.0	506.0	-0.27 (ns)
Kpandu	653.4	579.2	551.4	-0.47 ^b
Kumasi	681.0	664.0	604.0	-0.32 (ns)
Yendi	1 040.0	967.3	821.4	-0.46 ^a
Wa	915.1	854.3	812.5	-0.26 (ns)

^a Significant at 1%.

^b Significant at 5%.

(ns) = not significant.

75 mm was smaller than that for the other sites. Out of the two northern Ghana sites, a highly significant correlation was observed for Yendi but not significant at Wa in spite of a fairly high La Niña-El Niño seasonal rainfall difference of 102.6 mm.

20.3.1.1

ENSO Effect on Simulated Peanut Yield

The results of peanut yield simulation for Akatsi are shown in Fig. 20.1. The CDFs for the planting dates were not clearly separated from each other. However, the intermediate planting date (PD₂) resulted in the highest median yields for Kpedevi under all ENSO phases. At the same planting date however, median Kpedevi yields varied according to ENSO scenarios. Median yields of about 1 300, 1 650 and 1 700 kg ha⁻¹ were observed for El Niño, normal (or neutral) and La Niña conditions respectively (Fig. 20.1a-c). This trend is similar to that of rainfall noted earlier for Akatsi. In the case of Goronga, the CDFs for the planting dates again were not clearly separated particularly under El Niño conditions. However, PD₁ resulted in the highest median yield of about 1 600 kg ha⁻¹ for the El Niño phase. PD₁ again produced the maximum yield of about 2 500 kg ha⁻¹ under La Niña conditions while the best yield of 2 600 kg ha⁻¹ was obtained at PD₂ for the neutral phase (Fig. 20.1d-f). As for Kpedevi, given the same planting date, Goronga yields varied with ENSO phase. At PD₁ for example, 1 600, 2 500 and 2 400 kg ha⁻¹ yields were observed for El Niño, La Niña and neutral events respectively. El Niño median yield was at least 800 kg ha⁻¹ less than those of La Niña and neutral phases.

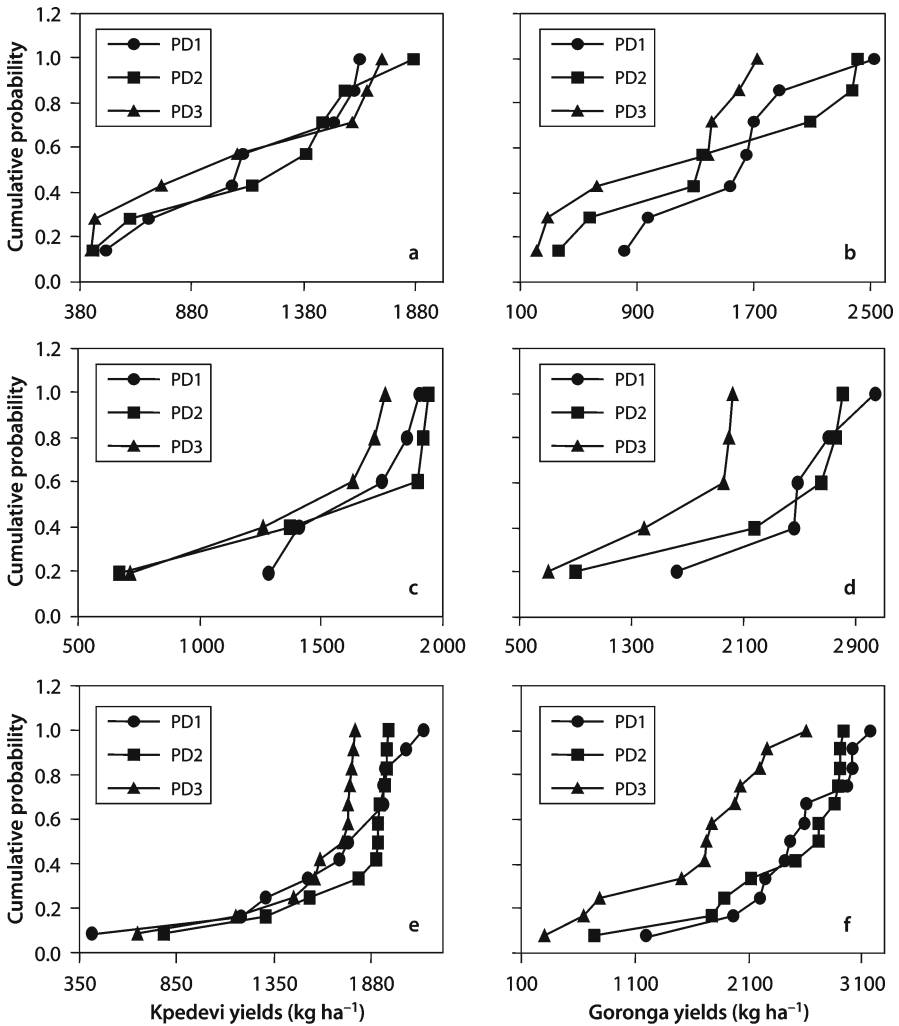


Fig. 20.1. Cumulative distribution functions of simulated peanut yields at Akatsi under varying planting dates and ENSO conditions; a 7 El Niño years; b 5 La Niña years; c 12 normal years; d 7 El Niño years; e 5 La Niña years; f 12 normal years

Seasonal rainfall for El Niño phase was observed to be appreciably lower than those for La Niña and neutral phases. The La Niña-El Niño rainfall difference was 182.4 mm and that for neutral-El Niño was 164.3 mm. This vast difference in moisture availability accounted for the appreciable yield reduction during El Niño seasons. La Niña and neutral phases had high (and fairly close) seasonal rainfalls with the La Niña-neutral rainfall difference being only 18.1 mm hence the similarity in yields.

20.3.1.2

Simulated Maize Yields

ENSO effect on simulated maize yields at Akatsi under varying planting dates and nitrogen fertilizer application rates is shown in Table 20.2. As noted for peanut, maximum mean maize yields (in boldface) occurred at varying planting dates for the various treatments. Also, at any given planting date and fertilizer rate, yields varied according to the ENSO phases. Fertilizer application generally resulted in increased output under all ENSO phases and at all planting dates. However, in all cases, increasing applied nitrogen rate from 0 to 60 kg N ha⁻¹ resulted in higher percent yield increases than for 60 to 120 kg N ha⁻¹. For example at PD₁, a yield increase of 305.6% resulted from 0 to 60 kg N ha⁻¹ increment compared with only 3.2% for 60 to 120 kg N ha⁻¹ under El Niño conditions. For La Niña, the yield increase was 384.9% compared with 22.1%, and for neutral 367.7% compared with 23.4%. Thus for fertilized maize production at Akatsi, early planting with a nitrogen fertilizer rate of 60 kg N ha⁻¹ gave the most profitable yield returns for all ENSO phases. Without fertilizer application, late planting showed best yield for El Niño years, early planting for La Niña and intermediate planting date for neutral seasons.

20.4

General Discussion

The lingering question is how to use ENSO phenomenon in agricultural planning in Ghana. As indicated earlier, one challenge is to establish that significant correlation exists between the ENSO phase and rainfall. Our limited analysis shows that indeed a significant correlation of seasonal rainfall with the pre-season ENSO phase with at least a 3-month lead time could be attained at some sites, but not all. How then do we improve the correlation skills? Given that Ghana's rainfall is also influenced by the Atlantic SSTs (Opoku-Ankomah and Cordrey 1994), further research may attempt to combine Atlantic and Pacific SSTs in seasonal rainfall forecast in Ghana. Using crop simulation modeling, we have also shown that indeed, peanut and maize yields at Akatsi can be clearly partitioned between the ENSO phases. Further, cropping strategies could be designed to exploit the forecast information. For example, early planting supported by modest fertilizer input would lead to significant higher yields in maize than any other strategy (Table 20.2). Without fertilizer input, however, late planting gave the best yields for El Niño. The final issue of concern is how to communicate ENSO information to end users (Extension Officers and farmers). This may require surveys of farmers' understanding of weather issues, weather schools, stakeholder meetings and actual field experiments to demonstrate the validity of ENSO-based cropping strategies. This aspect remains unexplored and research focus should be extended to such areas.

20.5

Conclusions

This study has investigated the effect of ENSO on seasonal rainfall amounts at nine farming sites in Ghana. Out of six sites in the south, there was a strong ENSO influence on seasonal rainfall at three sites namely Axim, Akatsi and Kpandu. In the middle

Table 20.2. Mean simulated maize yields (kg ha⁻¹) and percent yield increases as a function of ENSO phase and planting date

ENSO phase	N-fertilization rate (kg N ha ⁻¹)	Planting date (PD)/yield increase					
		PD1 yield	Yield increase (%)	PD2 yield	Yield increase (%)	PD3 yield	Yield increase (%)
El Niño	0	702.4	–	731.7	–	744.9^a	–
	60	2848.7	305.6	2142.3	192.8	2696.1	262.0
	120	2940.3	3.2	2696.4	25.9	3265.3	21.1
La Niña	0	682.2	–	676.8	–	540.6	–
	60	3307.8	384.9	2331.8	244.5	2030.4	275.6
	120	4038.6	22.1	3510.0	50.5	3575.0	76.1
Neutral	0	682.7	–	768.9	–	662.2	–
	60	3192.5	367.7	2790.3	262.9	2555.8	286.0
	120	3938.7	23.4	4003.4	43.5	4107.8	60.7

^a Highest maize yields with respect to planting date in boldface.

belt, ENSO influence was weak as observed for Kumasi. Seasonal rainfall at one out of the two northern sites (Yendi) showed strong ENSO dependence while at Wa, ENSO influence was not significant.

Simulation of peanut and maize under varying ENSO phases and planting dates showed that the intermediate planting date was best for Kpedevi irrespective of the ENSO phase. Under El Niño and La Niña early planting date was best for Goronga while the intermediate planting date was the preferred date under neutral conditions. The study suggests that ENSO-based seasonal forecast could be beneficial to agricultural planning at the farming zones considered.

Acknowledgements

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Application of Seasonal Climate Forecasts to Predict Regional Scale Crop Yields in South Africa

T. G. Lumsden · R. E. Schulze

21.1 Introduction

South Africa experiences a high interannual variability of rainfall which, in a region with abundant solar radiation, is the main determinant of year-to-year variations in crop yields. The coefficient of variation of annual rainfall ranges from less than 20% to about 40% across the country's arable area (Schulze 1997). As a result maize, which is the country's staple food, exhibits a coefficient of variation in annual yields ranging from less than 15% to over 60% (Schulze 2003). The variability in crop production has implications for food security in the country, particularly at household level amongst resource-poor farmers, whose livelihoods are heavily dependent on agriculture.

Seasonal climate forecasts are available for South Africa, the main source of operational forecasts being the South African Weather Service (SAWS). Although seasonal climate forecasts are being applied ever-increasingly in agriculture to aid in climate sensitive decision-making, efforts to do so are confined mainly to commercial agriculture. These efforts are to be encouraged and supported, since commercial agriculture is an important economic activity in the country and is the key to national and regional food security (du Toit et al. 1999). However, relatively little research is conducted to support the application of climate forecasts in decision-making in the small-scale/subsistence agriculture sector, where farmers are particularly vulnerable to the vagaries of climate.

The usefulness of climate forecasts for applications in agriculture can be enhanced if the forecasts are translated into agricultural outlooks, where the information is targeted for decision-making. Translation of climate forecasts into agricultural outlooks can be facilitated through the generation of crop yield forecasts using crop simulation models. This approach has the benefit of accounting for factors which affect crop growth that would not be represented in climate forecasts alone, such as antecedent soil moisture conditions and crop management practices.

Given the context described above, a desktop research project (Lumsden and Schulze 2004) was undertaken with the following objectives: (1) to research methodologies required to produce crop yield forecasts for small-scale/subsistence agriculture in South Africa, (2) to evaluate the quality (accuracy) of crop yield forecasts produced using the above methodologies, (3) to assess the potential to apply the crop yield forecasts to improve crop management decisions, (4) to make recommendations for further development of the products of the research and, using insights gained in the project, to make broader recommendations on future research and operational needs.

In this chapter the methodology developed to produce crop yield forecasts will be presented. The results shown will focus on the assessment of the potential to improve crop management decisions, given a crop yield forecast. Key recommendations emanating from the project will be discussed.

21.2 Study Area and Methodology

21.2.1 Crop Yield Model

Maize, being the country's staple food, was selected as the crop for which yield forecasts would be produced. The CERES-Maize (v3) growth simulation model (Tsuji et al. 1994) was used to simulate maize yield as it is well suited to account for the influence of crop management practices on yields.

21.2.2 Study Area

Maize yield forecasts were developed across various climatic regions of South Africa, where these regions were represented by selected Quaternary Catchments (QC). A QC is the smallest (fourth level) catchment subdivision used in general water resources planning in South Africa, and may be considered to be a relatively homogeneous natural response unit. The QCs, which generally range in area from 100 to 600 km², also represent a convenient scale for generating crop yield forecasts, as associated databases of climate and soil information to facilitate the production of the forecasts, are available at this scale. Fifteen QCs were selected for consideration in the study, these catchments being in poverty stricken former "homeland" regions where small-scale/subsistence farming is practiced and where household food security is lacking. The location of the QCs within South Africa is shown in Fig. 21.1.

The QCs represent a range in rainfall regimes and allow the yield forecasting methodology to be tested under a variety of conditions. Mean annual precipitation in the catchments varies from 330 mm to 910 mm, with the wetter areas being in the east and the drier areas in the west. The 15 selected catchments fall within the summer rainfall region of the country in areas where it is climatically feasible to grow maize (Schulze 2003).

21.2.3 Climate Forecasts and Downscaling

Several sources of operational climate forecasts, disseminated by both local and international institutions, were considered for use in this study. As a number of historical seasons were to be used in developing and testing the yield forecasting methodology, an archive of previously disseminated forecasts was required. The suitability of the forecasts was assessed in terms of several potentially limiting factors, these being, the lead time (seasonal), the number of historical seasons archived and the availability of corresponding observed daily data for use in forecast downscaling and verification.

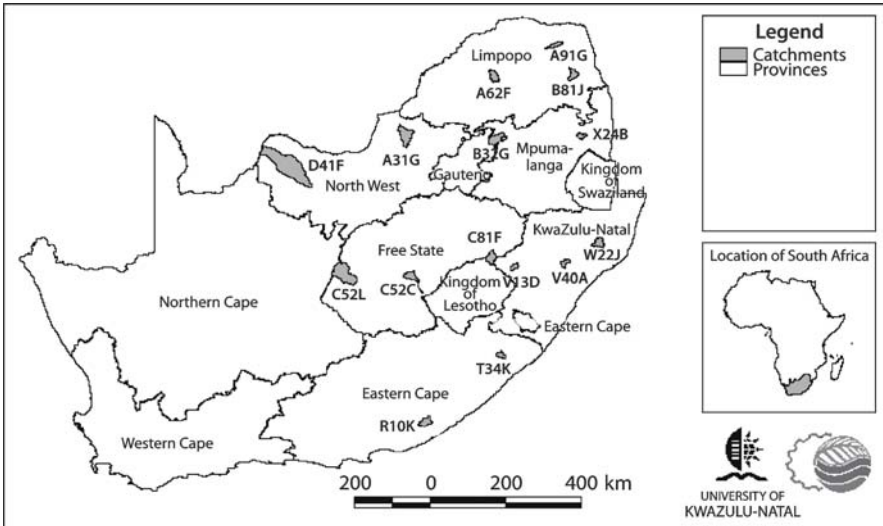


Fig. 21.1. Quaternary catchments selected for the generation of maize yield forecasts

The most suitable set of seasonal climate forecasts found was that produced by Landman and Klopper (1998) for the 1981/1982 to 1995/1996 seasons. These forecasts of seasonal rainfall were produced in an exercise to validate the statistical rainfall model used by SAWS in its operational forecasts. This model was developed using canonical correlation analysis, a regression-based technique considered to be at the top of the regression modeling hierarchy (Barnett and Preisendorfer 1987). The predictand in the model is December to March (summer) rainfall and the predictors are sea surface temperature anomalies from the global oceans between 45° N and 45° S for each of the four preceding three-month seasons (Landman and Klopper 1998). For large parts of the country, the December to March period forms a major portion of the annual rainfall (Tyson 1986; Schulze 1997). The rainfall model has not changed significantly since the study of Landman and Klopper (1998), apart from ongoing refinements. However, the format in which the forecasts are presented has changed from deterministic (single possible outcome) to probabilistic (three possible outcomes) format. Although the use of probabilistic forecasts is now generally encouraged in applications research (because it conveys associated risk), it was considered appropriate to use the deterministic forecasts published in Landman and Klopper (1998), as a relatively large number of seasons (15) were represented. For only three of these seasons (1993/1994 to 1995/1996), corresponding observed daily rainfall data were not readily available for use in this study. The rainfall forecasts were categorical in that rainfall was forecast to be either below normal, near normal or above normal. The rainfall forecasts were made for six regions of relatively homogenous (summer) rainfall distribution, these regions covering most of the country. The regions were originally defined by Mason (1998) and then updated by Landman and Klopper (1998). The observed categorical rainfall for each region and forecast period was determined by Landman and Klopper (1998).

The rainfall forecasts required both spatial and temporal downscaling in order to develop rainfall inputs to the CERES-Maize model. In the spatial domain, the rainfall forecasts needed to be downscaled from relatively large rainfall regions to QC scale, while in the temporal domain, they required downscaling from categorical rainfall for four month periods to daily rainfall values. Different methods of downscaling the rainfall forecasts were considered. The analogue season downscaling technique was selected as it is a relatively simple and robust technique in which the authors had previous experience in applying (Hallowes et al. 1999; Lumsden et al. 1999). The data/information required to apply this technique were available, whereas this was not the case for some other methods (e.g. applying a stochastic rainfall generator). The procedure adopted for downscaling rainfall forecasts (for the 1981/1982 to 1992/1993 seasons) was as follows: The categorical rainfall forecasts for a particular rainfall region were assumed to apply to each of the catchments falling within that region, i.e. an above normal forecast for the rainfall region implied an above normal forecast for each of the catchments in that region. The seasonal (December to March) forecasts for a catchment were then downscaled to daily values of rainfall by selecting all historical seasons in that catchment's rainfall record that represented the forecast concerned, i.e. if the forecast for a season was for above-normal rainfall, then all historical seasons experiencing above-normal rainfall were selected to represent the rainfall record for that season. For each catchment, a single rainfall station having a rainfall record representative of the catchment, had previously been selected. Above normal, near normal and below normal classes of rainfall corresponded to the upper, middle and lower terciles, respectively, of the long-term probability distribution of seasonal (December to March) rainfall. For each catchment, thirty seasons (1950/1951 to 1979/1980) of observed rainfall were extracted from the QC climate database to serve as analogues to represent the above normal, near normal and below normal rainfall terciles. Data were extracted for this period as it allowed for an equal number of seasons to represent each tercile, i.e. ten seasons per tercile. Only seasons prior to the first season forecasted (1981/1982) were considered for use as analogue seasons. When preparing CERES-Maize climate input files to represent a seasonal forecast, ten individual climate files were created, each of these corresponding to a different analogue season. This implied that there were multiple yield outcomes for a season, which could then be considered a forecast yield distribution.

21.2.4

Crop Yield Simulations Performed

Nine different crop management strategies were represented in the crop yield simulations performed. These strategies consisted of all combinations of 3 different planting dates and 3 different plant populations. The choice of planting date and plant population for a season are important management decisions that can be altered relatively easily in response to a seasonal climate forecast to potentially improve yields for that season. The plant populations considered were categorized as either low (15 000 plants ha⁻¹), medium (25 000 plants ha⁻¹) or high (35 000 plants ha⁻¹), and were applied to all catchments. The planting dates considered for the various catchments were categorized as either early, average or late. The average planting date for a catchment was set to be equivalent to the long-term climatically optimum planting date for

that catchment, as determined by Schulze (2003). The respective early and late planting dates for the catchment were then set to be one month before and one month after the average date. The early, average and late planting dates for the various catchments are shown in Fig. 21.2.

The potential for crop yield forecasts to improve crop management decisions was assessed over the 1981/1982 to 1992/1993 seasons by comparing: (1) the yield that would have been obtained if crop management strategies were selected according to yield forecasts, i.e. the yield of the forecast selected strategy, versus (2) the yield that would have been obtained if management strategies were selected according to long-term yield performance, i.e. the yield of the long-term strategy. It was assumed that in the absence of a yield forecast, a farmer would have selected his crop management strategy based on the long-term yield performance of the different strategies. In a particular catchment, the long-term strategy was the same for each of the 12 seasons considered, while the forecast selected strategy varied for the different seasons. The forecast selected and long-term strategies were compared on a seasonal basis, with the yields being simulated by CERES-Maize using the observed daily rainfall record for the season concerned. If the forecast selected strategy outperformed the long-term strategy, then it is assumed the farmer would have benefited from crop yield forecasts, provided he/she heeded them.

Before the above comparisons could be made, the forecast selected and long-term strategies had to be identified for each season. Yield forecasts were produced using the appropriate analogue rainfall season records identified previously during the downscaling of the SAWS rainfall forecasts. To identify the forecast selected strategy for a season, the medians of the forecast yield distributions of the 9 crop management strategies simulated were compared, and the highest yielding strategy identified. Simi-

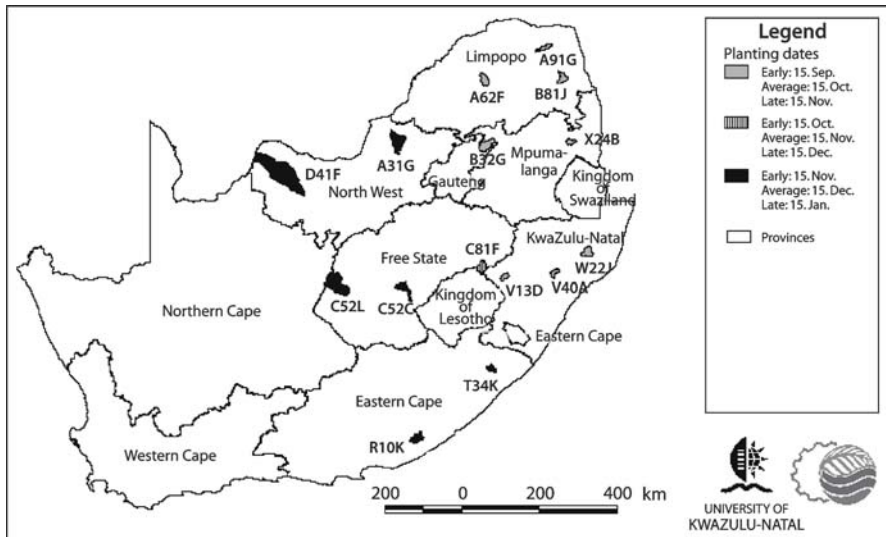


Fig. 21.2. Planting dates used in maize yield simulations

larly, to identify the long-term strategy, the medians of the long-term yield distributions (derived from historical yield simulations for the 1950/1951 to 1979/1980 seasons) of the 9 strategies, were compared, and the highest yielding strategy identified.

21.2.5

Crop Model Inputs

The date of generating yield forecasts was set to be one month prior to planting. This was assumed to be the minimum lead time required to be able to alter management decisions in response to a forecast, and is possibly also a convenient lead time for regional scale planning. As the rainfall forecasts used in maize yield forecasting were valid for the period from December to March (inclusive), there were periods before and after this period for which rainfall data were required in order to simulate yields in the various QCs, but for which no observed rainfall data would have been available at the time of making a forecast (in an operational context). It was thus necessary to consider ways of filling these periods with representative rainfall data. While 3-month categorical forecasts were produced by Landman for September to November and November to January, these forecasts were shown to have low accuracy and were not available for all seasons required (Hallowes 2002). It was thus decided that the analogue seasons used to represent the December to March period would also be assumed to be representative of the entire growing season, and for the one month period prior to planting.

Daily inputs for the other climate variables required by the CERES-Maize model, namely maximum temperature, minimum temperature and solar radiation were derived from monthly mean data (Schulze 1997) translated into daily values by a Fourier Analysis. Daily observations of these variables were not readily available at QC level.

As chemical fertilizers are generally too expensive for small-scale/subsistence farmers, the application of manure as a substitute was used in the crop yield simulations. A manure application rate of 4000 kg ha⁻¹ and a nitrogen content of 1.13% were assumed for all crop management strategies, based on information in van Averbek and Yoganathan (1997). The 9 management strategies were represented as individual treatments in the "Experimental Details" input file utilized by CERES-Maize. A medium season-length dryland maize cultivar, PAN 6479, was used in all maize yield simulations as it is recommended for planting throughout the summer maize growing regions of the country (Pannar 2006). The model simulations were started on 1 June of each season, with observed climate data being used up to the date of forecast to initialize the soil water and nutrient balances.

As the focus of this study was on adapting crop management practices to seasonal climate variability for different climatic regions in the country, it was decided that a single common soil type would be assumed for all the catchments. This ensured that the analysis of simulation results was not obscured by the influence of different soil types, but was focussed on the interaction between climate and management. A medium textured sandy loam soil with a depth of 0.6 m was assumed for all catchments. A shallow soil depth was selected as this was deemed typical of small-scale/subsistence agriculture in South Africa.

21.3 Results

The frequency with which forecast selected strategies outperformed long-term strategies, and *vice versa*, over the 1981/1982 to 1992/1993 seasons is presented in Fig. 21.3 for each catchment. The frequency with which the two selected strategies performed equally well, is also shown. The provinces in which the catchments are located are shown at the top of the figure to indicate geographic locality.

The frequency with which forecast selected strategies performed better than long-term strategies ranged from 0 to 75% across the different catchments. The outcome whereby forecast selected strategies performed better than long-term strategies was the most frequently occurring outcome in three catchments, these being located in KwaZulu-Natal province. In contrast, the outcome whereby long-term strategies performed better than forecast selected strategies was the most frequently occurring outcome in two catchments in Mpumalanga province. In the remaining 10 catchments, the outcome whereby forecast selected and long-term strategies performed equally well, was the most frequently occurring outcome or, alternatively, was equal in proportion to the outcome of long-term strategies performing better.

Figure 21.3 indicates the frequency with which a certain strategy performs better than another, but does not give any indication of the extent to which its yields are higher. This was assessed in Fig. 21.4 for cases where the forecast selected strategies yielded more than the long-term strategies. The maximum, mean and minimum differences in yield between the two strategies, over the 12 seasons of simulation, are plotted in the graph for the relevant catchments. The mean differences in yield are also shown in brackets as a percentage, with the relevant number of data points indicated

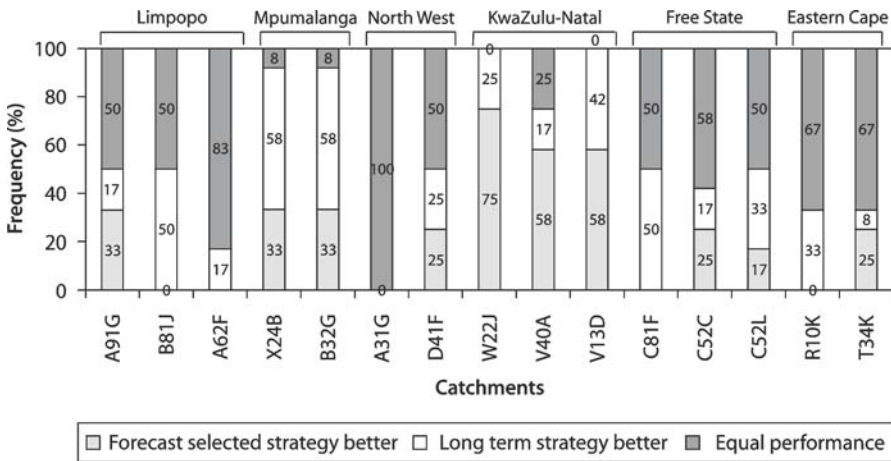


Fig. 21.3. Frequency with which different crop management strategies performed better over the 1981/1982 to 1992/1993 seasons

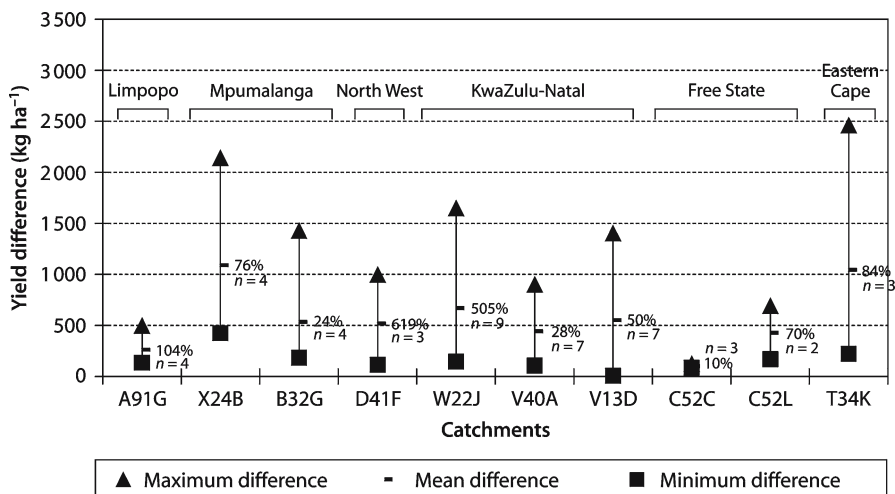


Fig. 21.4. Differences in yields obtained from forecast selected and long-term strategies (cases where forecast selected strategies yield more than long-term strategies) over the 1981/1982 to 1992/1993 seasons

below. The provinces in which the catchments are located are again shown at the top of the figure. Figure 21.4 shows that the mean differences in yield for the catchments in KwaZulu-Natal (where forecast selected strategies performed better than long-term strategies most frequently) ranged from 28 to 505%. The mean yield difference for catchment W22J, when expressed as a percentage (505%), is inflated as a result of two seasons of crop failure when applying the long-term crop management strategy in this catchment. Nevertheless, the mean yield difference, when expressed in kg ha^{-1} (670), has the same order of magnitude as the other KwaZulu-Natal catchments, and the forecast selected crop management strategy can be concluded to have performed appreciably better than the long-term strategy in this province. The yield differences in the other provinces are also appreciable, although it should be borne in mind that there were considerably fewer occurrences of the forecast selected management strategy outperforming the long-term strategy (cf. Fig. 21.3).

21.4

Discussion and Recommendations

The usefulness of the crop yield forecasts, as defined by their potential to improve crop management decisions, varied across the catchments assessed, with the greatest forecast usefulness being detected in KwaZulu-Natal province. The gains in yield derived from applying yield forecasts in this province were also shown to be appreciable.

Ideally, climate forecasts should be available for the entire growing season when generating crop yield forecasts. In this study, rainfall forecasts were only available for the December to March period, while many of the crops simulated were growing outside of this period, thus requiring assumptions to be made about the rainfall in these periods. The yield forecasting methodology needs to incorporate current climate fore-

cast formats (terciles with associated probabilities), and the usefulness of the resulting yield forecasts needs to be assessed. If there are an insufficient number of forecast seasons for this analysis, as was the case in this study, an historical set of climate forecasts could be generated retrospectively. The incorporation of general circulation model (GCM) derived climate forecasts in the yield forecasting methodology also needs to be assessed, as these are becoming more readily available for South Africa. GCM derived climate forecasts may have advantages over forecasts derived from statistical climate models. For example, the finer spatial and temporal scale of modeling in GCMs produces information in a format more suited to application in crop yield models.

Crop forecasts were only produced for maize in the current study. Forecasts could be produced for other crops, which would then allow for crop selection to be included in crop management recommendations. Crop management strategies giving rise to the highest maize yield were selected in the study. In practice, a small-scale/subsistence farmer's objective may not be to maximize yield, but rather to minimize risk. To minimize risk, a farmer could avoid adopting strategies that give rise to a wide range in yields under different seasonal climate conditions, thus minimizing the impact of a forecast being wrong. Farmers apply a variety of management practices to spread the risk of a particular strategy failing. As confidence in the forecasts grows, forecast selected strategies could be applied more extensively.

In practice, many factors influence a farmer's crop management decisions. It is recommended that the application of crop yield forecast information in crop management decisions be assessed in more detailed case studies where these factors can be taken into account. Field data would need to be collected to ensure that the crop model inputs, including the representation of crop management strategies, is realistic. Observed data would also be needed to verify forecast accuracy and usefulness. Greater collaboration with stakeholders would be required to facilitate these case studies. A research project has been proposed involving a number of organizations and individuals, where case studies will be implemented at identified sites in various provinces.

Lumsden and Schulze (2004) reviewed forecast information needs and forecast application constraints in South Africa. These needs include improved forecast quality, more extensive forecast verification, more relevant forecasts to users, forecast dissemination improvements and capacity building. Apart from these deficiencies in the available forecast information, farmers may also be constrained in their ability to respond to forecasts owing to a lack of resources such as draft power, healthy labor in HIV/AIDS affected communities, credit, water, land, fertilizers and favorable markets. The impact of these constraints on forecast application could be better understood in the case studies planned above. Efforts to improve the resources available to farmers need continued attention.

Based on the findings of the Lumsden and Schulze (2004) study, which included a review to determine what forecast information is currently available for South Africa, three potential applications of crop yield forecasts to small-scale/subsistence agriculture were identified for further research and implementation in the country. These applications, which have varying scales and functions, are outlined in Table 21.1.

An example of regional planning where crop yield forecasts might be applied is the coordination of aid to farmers. For regional planning, magisterial districts were suggested in Table 21.1 as an alternative to QCs as the scale at which forecasts could be produced. Although QCs are a convenient scale at which to produce forecasts because

Table 21.1. Potential applications of crop yield forecasts to small-scale/subsistence agriculture identified for further research and implementation in South Africa (Lumsden and Schulze 2004)

Yield forecast application	Scale of yield forecast	Potential users	Representation of soils	Representation of management
(1) Regional planning	Regional – QC, or – magisterial district	– Government departments – NGOs – Sector organisations	Typical soil type and depth	Generic strategy
(2) Regional crop management recommendations	Regional – QC, or – magisterial district	Extension services	Matrix of common soil types and depths	Regional strategies
(3) Local crop management recommendations	Local – extension center – representative farms	Extension services	Actual soil type and depth	Local strategies

of the associated agroclimatic databases available, this scale of forecasting may not be convenient for users. A single typical soil profile and a generic crop management strategy would be used as the influence of different soils and management strategies are of less importance for this application. According to Vogel (2000), the application of forecast information in regional planning may be the most feasible application of forecasts if the constraints faced by farmers in altering their crop management strategies in response to a forecast, are found to be too great. The production and dissemination of crop yield forecasts for regional planning is believed to be the most achievable of the forecast applications identified in Table 21.1.

For the forecast application targeted at regional crop management recommendations, magisterial districts were again suggested as an alternative to QCs as the scale at which forecasts could be produced, for the same reasons discussed above. A matrix of soil types, soil depths and crop management strategies would be represented in these forecasts in an attempt to represent the range of conditions occurring in the region. The regional crop management strategies would be focussed on management practices less subject to local effects, for example, planting dates and crop type selection. The crop yield forecasts produced in the current study would fit into this category of forecast applications. The Directorate of Agricultural Risk Management in the National Department of Agriculture (NDA-ARM) periodically disseminates regional agricultural advisories to farmers via extension services. At present the advisories include simple crop management recommendations based on climate forecasts and reports on current conditions from field workers. Crop yield forecasts like those produced in this study could be used as an additional source of quantitative information in formulating these advisories (Archer, personal communication in 2003; Walker, personal communication in 2003; Lumsden and Schulze 2004).

For the forecast application targeted at local crop management recommendations, agricultural extension centers/offices are suggested as possible sites for forecasting because the relevant extension officers would be familiar with the conditions prevailing at these centers. Alternatively, representative farms in the extension districts could be identified for yield forecasting, as farmers might find it easier to relate the condi-

tions on these farms to their own farms. The actual soil type and depth would be represented in the forecasts, as would crop management practices that are specific to the area. At this scale of application it might be possible to begin tailoring the recommended management responses to suit the typical livelihoods of households found in the area. The detailed case studies proposed previously would fit into this category of forecast application. While recommendations at this scale would be more applicable to farmers, a greater degree of downscaling of the climate forecast information would be required, which may limit the usefulness of the resulting yield forecasts. If the case studies prove successful, the sites studied could become demonstration sites showing the value of applying forecast information in decision-making. The widespread production of crop yield forecasts at this scale would be a longer term goal because of the research and resources required.

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Climate Information for Food Security: Responding to User's Climate Information Needs

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22.1

Introduction

Ensuring household food security in a rainfed agricultural livelihood requires availability of climate information regarding onset of seasonal rains allowing for timely preparation for planting. Due to increased irregularity of the onset, amount and length of seasonal rains, the prediction of onset of seasonal rains at sufficient lead times is increasingly becoming a very critical issue for farmers. Currently climate scientists are able to use sea surface temperatures as scientific indicators, to forecast rainfall amounts of above normal, normal and below normal averaged over a period of three months. Whereas this type of information is important, the primary climate information need of the farmers is knowing in advance the expected onset of seasonal rains. As a coping mechanism, farmers attempt to use their traditional indicators, particularly local winds and temperatures, to forecast this important climate element. However, identification, validation and improvement of these indicators had not been done. As a synergy to the farmers practice, records of winds, temperature and rainfall from the existing synoptic weather stations can be used to study these relationships on scientific basis. Although analysis of pentad rainfall totals of records from some of the existing weather stations have been done indicating onset of seasonal rains on average basis, practically these seasonal rains set in at different periods of each year. Currently there is no availability of models to predict the different periods when the rains can set in.

Therefore this study identifies details of how farmers traditionally use local temperatures and winds to forecast onset of first rains; validate the indigenous rainfall indicators for onset of first rains; and develop statistical models for forecasting of first rains. Identification of usage was achieved through conducting individual and group surveys of farmers in eastern (Tororo), Lake Victoria basin (Jinja), central (Wakiso) and western (Masindi) Uganda. Validation of indigenous rainfall indicators is based on the climate data from synoptic weather stations in the four regions. Model development was achieved by statistical linear regression of validated temperature and wind indicators with rainfall onset dates formatted in pentads.

22.2

Methodology

The research study needed two types of data. The first was the indigenous meteorological knowledge of farmers. In order to capture these data, a field survey was conducted using a questionnaire that interviewers used to ask farmers about their

knowledge related to local meteorological issues. The second type of data consisted of historical meteorological data acquired from the weather stations within the survey areas.

22.2.1

Survey Sites

The geographical coordinates of the sites (Table 22.1) indicate that all the survey areas are located north of the equator, Masindi being the farthest from the equator (Fig. 22.1).

22.2.2

Field Surveys

Field surveys were conducted in Masindi, Wakiso, Jinja and Tororo districts. The choice of districts was mainly due to the presence of operational weather stations with long-term historical data namely Masindi, Namulonge, Jinja and Tororo respectively. Secondly the surrounding farming communities had some fair indigenous meteorological knowledge. An area collaborator working in the field of agriculture and residing in the districts was identified for each district. These collaborators had the role in assisting the research team in identifying research assistants and farmers to participate in the survey.

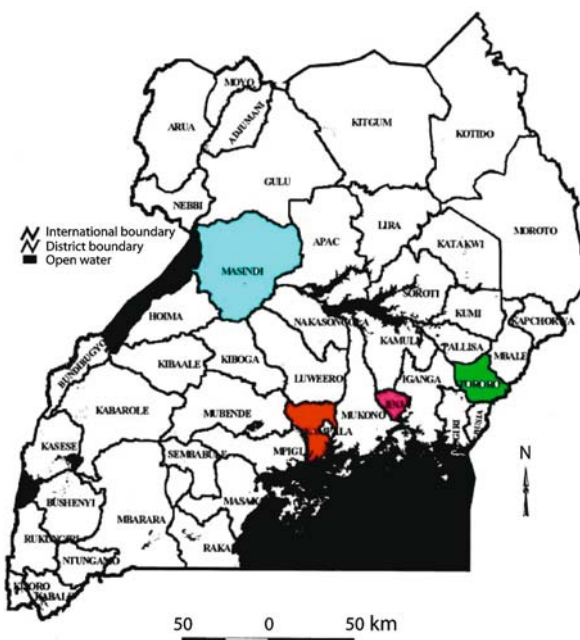
The research team developed a questionnaire as a survey instrument. The questionnaire was pre-tested in Jinja district after which corrections were made for the survey. A workshop of two days was conducted in Jinja for the research assistants who were identified to participate in the research study. The workshop was intended to enrich the research assistants with basic knowledge on both scientific and farmers' meteorological knowledge as well as reviewing the questionnaire.

The field surveys were conducted during the dry season months of January and February 2003. About 60 farmers in Masindi and Wakiso districts were interviewed. In Jinja and Tororo Districts 90 and 80 farmers, respectively were interviewed. The area collaborator for each place identified the participants with preference to elderly ones. Each survey took three days, and the interview was conducted in local languages. While interviewing the research assistant translated the questions in English into the local language. The responses in the local language were then translated to English. This was achieved through selecting research assistants who either worked or resided in the survey areas.

After the field surveys the answers in the questionnaires were computerized. Data entry operators were contracted to enter the data using Microsoft Excel software, following a designed format. The data were then coded for statistical analysis using the SPSS software. In order to harmonize the local words used in the survey areas with what was recorded in English, the survey areas were revisited to get further explanations from farmers. After the analysis hypotheses were derived from the findings related to how farmers use local atmospheric indicators to forecast the onset of the 1st wet seasonal rains.

Table 22.1. Geographical position of the survey sites

Station	Longitude (°E)	Latitude (°N)	Altitude (m)
Masindi	31.7	1.7	1147
Namulonge	32.6	0.5	1130
Jinja	33.2	0.5	1175
Tororo	34.2	0.7	1170

Fig. 22.1. Survey district sites are shown on the map of Uganda

22.2.3

Weather Station Data

In order to test the statistical validity of the knowledge and experience of how farmers use atmospheric indicators to forecast rains, records of local atmospheric conditions were needed. In this study data collected at the weather stations Masindi, Namulonge, Jinja, and Tororo belonging to the Uganda Department of Meteorology were used.

Daily weather data on precipitation, temperatures and winds were observed by meteorological observers at each of the stations and recorded on paper forms. The records are then sent to the headquarters of the meteorology department in Kampala where they are stored in the archive. In some stations a copy of the records is usually kept at the weather station.

The meteorological data set considered for this study included the period 1960 to 2003. Although some rainfall data were available in electronic medium, the majority of the data needed data entry, especially temperatures and winds. Daily temperatures, winds and rainfall data were entered using Excel spreadsheet software. Analysis of the computerized data revealed many gaps especially during the years 1975 to 1989. This was basically due to the number of civil wars which Uganda has gone through during those years. In light of the above problem, there was no continuous data set from 1960 to 2000.

Although the standard data set recommended for statistical analysis is 30 years (1960–2000), in this study a minimum of 10 years of recent continuous data set was considered. Therefore specific criteria were set as to how the limited data could be used for analysis. First the data set for analysis and development of a model should be for recent years from 1989 to 2003, since this should fairly reflect the recent climate. Due to the nonstationarity of meteorological observations, Nicholls (1984) highlights the need to use recent data to derive forecast equations. Secondly in order to get significant relationships, high cut off values of correlation of $r = \pm 0.63$ ($P < 0.05$) and $r = \pm 0.76$ ($P < 0.01$) were set as shown in Table 22.2.

Using excel software, the daily rainfall data for each station was smoothed using Pascal's 5-point coefficient weights. Based on the criteria in Table 22.3, the INSTAT software was used to determine the different historical onset dates for the first rains. The daily maximum temperatures for each station were smoothed using a 5-point coefficient weights. The smoothed data were then processed into 5-day average tem-

Table 22.2. Significant correlations values

Data set	$P = 0.05$	$P = 0.001$
30	0.360	0.460
25	0.390	0.500
20	0.440	0.570
15	0.510	0.640
10	0.630	0.760

Table 22.3. Criteria for determining the date onset of rains

Criteria	Option 1	Option 2
Earliest start date ^a	45	45
Threshold for rain (mm) ^b	2.45	4.95
Rain days ^c	5	5
Total rainfall (mm) ^d	20	20
Days with rainfall ^e	3	3

^a The date when the first rains may set in early.

^b Minimum amount of rain to be considered a rain day.

^c Number of consecutive days considered for analysis.

^d Minimum expected rainfall amounts in five consecutive days.

^e Minimum number of rainy day out of five consecutive days.

perature values. The arrays of onset dates were then correlated with the arrays of maximum and minimum temperature average values. Since the objective of the study was to identify within which period of the dry season is the maximum temperatures related to onset dates, the correlations were run from the dry period of November up to February. Once periods of maximum temperature significantly related to rainy season onset were identified, regression analysis was performed to develop predictive models for each site.

22.3 Results

The findings in this study were outlined district per district, first reporting on the survey findings followed by statistical analysis.

22.3.1 Characteristics of Survey Areas

Local expertise on indigenous knowledge may be influenced by a person's livelihood, gender, age and education. As regards to gender, in each of the sites, more men than women participated in the survey (Table 22.4). The percentage of men ranged from 73% in Namulonge to 81% in Tororo. The women ranged from 19% in Tororo to 27% in Namulonge.

Elderly people are assumed to be the custodians of indigenous knowledge and hence a majority of elderly people were included in the survey. The percentage of respondents over 40 years of age ranged from 55% in Jinja to 89% in Namulonge (Table 22.4).

22.3.2 Crop and Livestock Production Systems

Table 22.5 reveals that cereal crops were the main crops grown in each of the survey sites. Masindi, Wakiso and Jinja have perennial crops like coffee. Most of the crops like maize, cassava, beans, bananas, and millet double as both cash and food crops. Rains influence cereal crops, which implies that both household food supply and income are affected by the performance of the seasonal rains. The rankings were done with respect to major crop in the region.

Table 22.4. Percentage of gender representation and age range of respondents

Site	Female	Male	Age range		
			20–30 yr	40–50 yr	60–80 yr
Masindi (60)	23	77	31	39	30
Namulonge (60)	27	73	10	47	42
Jinja (80)	23	77	45	44	11
Tororo (80)	19	81	16	35	49

Table 22.5. Main cash crops and food crops for each site

Rank	Namulonge	Jinja	Tororo	Masindi
Cash crops				
1	Coffee	Coffee	Cotton	Tobacco
2	Maize	Maize	Millet	Coffee
3	Cassava	Beans	Maize	Rice
4	Banana	Sweet potatoes	Cassava	Cassava
5	Beans	Tomatoes	Rica	Beans
Food crops				
1	Sweet potatoes	Maize	Millet	Cassava
2	Banana	Beans	Cassava	Sweet potatoes
3	Maize	Sweet potatoes	Maize	Millet
4	Cassava	Bananas	Sorghum	Beans
5	Bean	Cassava	Sweet potatoes	Bananas

22.3.3

Rainfall Seasons in the Survey Areas

In general the rainfall patterns experienced in all four of the sites is bimodal i.e. they experience two rainfall seasons and two dry seasons. Figure 22.2 indicates the average monthly rainfall for each site. The light gray color indicates months with rainfall amount below 100 mm. The dark gray color indicates months with rainfall amounts above 100 mm, which is considered as wet months. On average, the first rains stretch in March to May and the second rains from September to November. Basalirwa et al. (1993) findings reveals the sites Masindi and Tororo have different climate zones while Jinja and Wakiso are the same climate zones. As such at each site there are differences in terms of onset dates, rainfall amounts and duration. For example Fig. 22.2 reveals that Masindi has shorter duration of the first rains compared to the rest of the sites and Tororo has more seasonal rainfall amounts.

22.3.4

Production Problems

From the major production problems at the four study sites (Table 22.6), it can be seen that climate risks rank as one of the five major problems faced at all the four sites. At Tororo, climate issues rank as the number one production problem while at the rest of the three sites, climate issues follow pests and diseases.

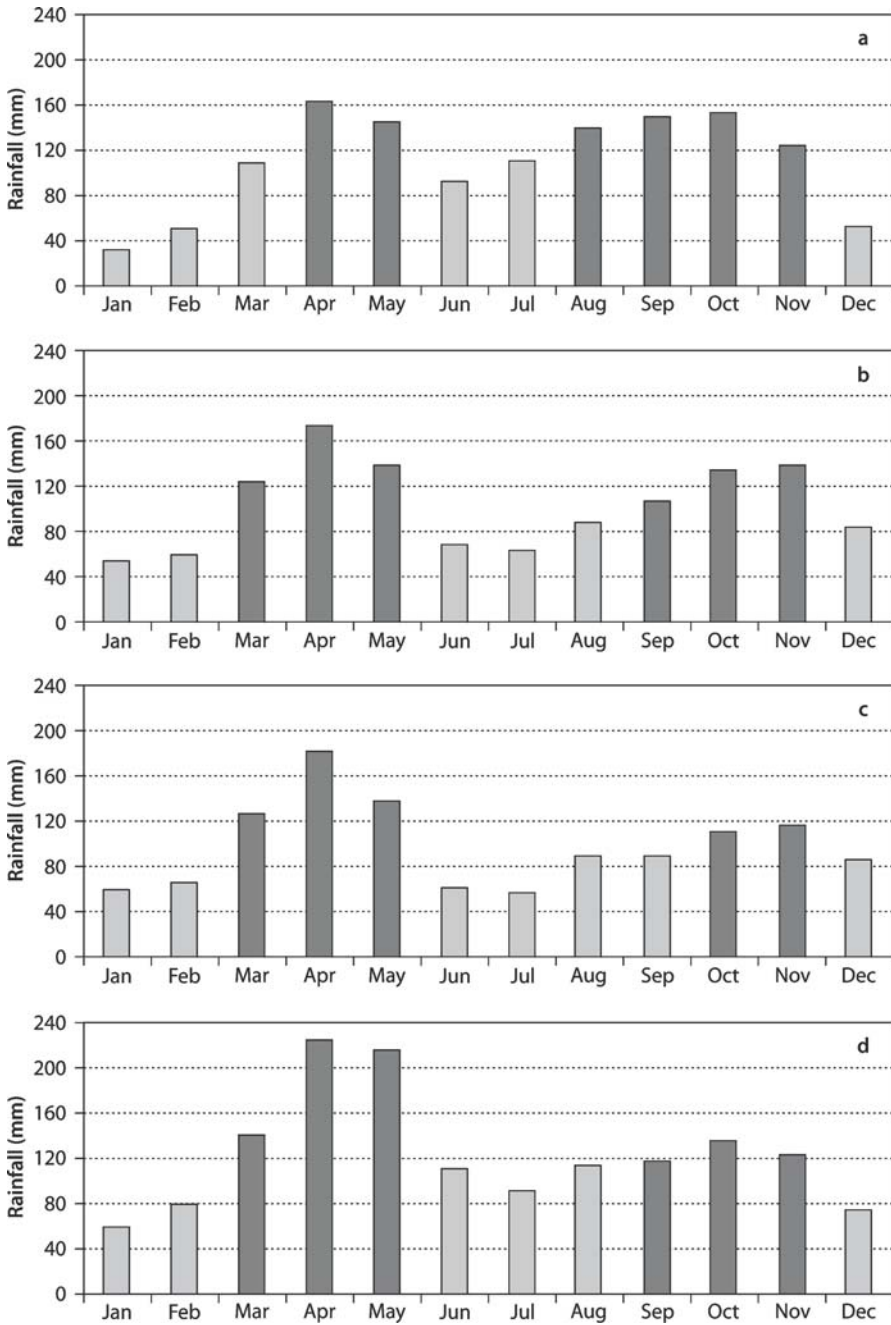


Fig. 22.2. Average monthly rainfall (mm) at; a Masindi; b Namulonge; c Jinja; d Tororo

Table 22.6. Major production problems at each site

Rank ^a	Masindi	Wakiso	Jinja	Tororo
1	Pests and diseases	Pests and diseases	Pests and diseases	Climate issues
2	Climate issues	Climate issues	Climate issues	Labor shortage
3	Labor shortage	Markets	Markets	Pests and diseases
4	Markets	Land pressure	Land pressure	Markets
5	Land pressure	Labor shortage	Labor shortage	Crop varieties

^a Ranking is based percentages facing the problem 1 – highest %, 5 – lowest %.

The major climate issues affecting the farmers include droughts, floods and hailstorms, erratic rains and delayed onset of rains. These affect the farming activities like harvesting, planting, grazing, plowing, weeding, watering, etc.

22.3.5

Indigenous Rainfall Indicators

Farmers have developed different approaches in responding problems related to rainfall.

22.3.5.1

Determining the Right Planting Time

The main criteria farmers in these regions use to determine the right time for planting their crops are rainfall onset followed by the calendar months (Table 22.7). At the onset of the rains, the farmers, wait for at least 2–3 showers then they consider planting their seeds. However the onset of rains should be within the expected months for planting. For example for this region, the showers should begin, in the months of late February or early March.

Other criteria include winds blowing westwards, rising temperatures and development of cloud cover.

22.3.5.2

Major Rainfall Indicators Farmers Use to Forecast Onset of First Rains

The main five rainfall indicators farmers use to forecast rains are winds, temperatures, clouds, birds and trees (see Table 22.8). The winds, temperatures and clouds are common atmospheric elements observed by both meteorologists and farmers. However unlike the farmers who keep the records in their minds, the meteorologists observe and keep the records on different mediums like paper and computer, which can facilitate follow up analysis.

Table 22.7. Farmers indicators of right planting time in different regions

Serial number	Indicator	Masindi	Wakiso	Jinja	Tororo
1	Rainfall onset	62	42	34	15
2	Calendar months	27	40	31	
3	Trees shade leaves		5		48
4	Clouds darken	6	7	9	25
5	Soil gets wet	10	2		
6	Winds blow eastwards			11	20
7	Winds blow westward		8		1
8	Winds blow southwards	2	4		4
9	Winds change direction	3	2		
10	Temperature increase		7	10	1
11	Birds movement		5	1	8
12	Radio climate forecasts			3	
13	Moon shape	2			7
14	Thunder and lightening			1	3

Table 22.8. Major rainfall indicators used by farmers to forecast onset of first rains

Rank	Indicator	Masindi	Wakiso	Jinja	Tororo
1	Winds	73	41	55	78
2	Clouds	49	31	46	55
3	Thunder	29	12		16
4	Temperatures	21	36	29	36
5	Moon	21	3	1	
6	Insect	14	15	1	
7	Trees	11	17	4	3
8	Birds	11	17	9	4
9	Mountain	6			
10	Mist	2	3		
11	Humidity			13	
12	Months		7	1	

Although, farmers have a range of local indicators, there are specific indicators that are regarded as more reliable than others. Table 22.9 reveals that the most reliable indicators are temperatures, winds, clouds and birds.

22.3.5.3

Forecasts of Rains by Farmers

Table 22.10 reveals that the majority of farmers find it easier to forecast the first rains than the 2nd seasonal rains. This is contrary to meteorologists who find it easier to forecast 2nd rains than 1st rains.

The ability of farmers being able to forecast 1st rains could provide scientific clues to meteorologists to forecast the rains better.

Table 22.9. Reliable indicators used by farmers to forecast onset of rains

Indicator	Masindi	Wakiso	Jinja	Tororo
Temperatures	13	39	61	13
Winds	77	29	45	79
Birds		17	6	4
Clouds	51	16	15	63
Insects	5	12		
Trees	2	8		1
Frogs		5		
Months		3	1	
Mist		3	1	1
Moon	5	2	3	
Mountain	3			
Lightening	21			15
River Nile			3	
Radio			3	
Humidity				3

Table 22.10. Percentage of farmers forecasting the first and second seasonal rains

Rainfall season	Survey sites			
	Masindi	Wakiso	Jinja	Tororo
1st season	79	71	91	93
2nd season	20	8	1	6
Both seasons		14	1	

22.3.5.4

Local Wind Systems

Farmers have a range of names they give to the winds they observe in their region. The names are based on direction of the winds, place of origin and speed. For example in Wakiso the wind locally known as Walusi, blows southwards from a hill called Walusi. Another type of wind in Wakiso is Kikunguta associated with a high speed of wind. This indicates that farmers are observant of subtle details of wind dynamic and may relate to their use as rainfall indicators

22.3.5.5

Time of Appearance of Wind Indicators

Most often the winds used for rainfall forecasts exhibit themselves in the month of February followed by March (Table 22.11). At times the winds appear in December and January. This means that these indicators can be used to forecast onset of first rains using mainly February winds and sometimes as early as December and January winds.

22.3.5.6

Operational Use of the Winds

The operational use of the wind indicators is based mainly on the change of wind direction. During dry season the wind blow in a particular direction and as the season is about to begin, the wind direction changes. Results show that directionality noted by respondents could be almost any combination. The direction and speed of winds are important features farmers use to forecast seasonal rains. During the January–March dry season, the winds usually blow strongly westwards. As the seasonal rains are approaching, the winds change direction, and blow eastwards. Winds blowing eastwards are heavily linked with the onset of seasonal rains. The above farmers' observations are consistent with findings by Camberlin and Wairoto (1997) and Okoola (1999). As such observing the time of the year when the winds change direction from blowing westwards to eastwards of the region could be used to forecast ahead of time when seasonal rains may start.

In addition to winds, farmers experience different temperature conditions in their place. These conditions have their local names as shown in the Appendix (Tables A22.1–A22.4). The names of the local temperature conditions are associated with the humidity, time

Table 22.11. Percentage occurrence of winds

Month	Masindi	Wakiso	Jinja	Tororo
December	23	2	9	15
January	49	8	33	34
February	64	49	45	85
March	64	12	18	60

of temperature increase and decrease. As shown in Table 22.12 below, the majority of farmers use the increase in temperatures during a dry season as signals for early onset of first rains. In Masindi, there is a clear indication that increase in temperature indicates early onset while a temperature decrease indicates late onset of first rains. The same indication is reflected in Wakiso, Jinja and Tororo sites. However apart from Masindi, which associates a clear decrease in temperatures with late onset, at the rest of the sites no such association was seen.

The occurrence of these temperature conditions is mainly in the month of February followed by March (Table 22.13). This suggests that the temperature conditions in February could be used to forecast onset of first rains. Though the farmers use February temperatures to forecast first rains a week ahead, there is potential for application of this predictor in the month of January.

22.3.5.7

Lead Time at which Farmers Make Forecasts of Onset of First Rains

The survey indicated a wide range of lead-times at which farmers can forecast onset of first rains. Table 22.14 shows that the majority of farmers in Masindi, Wakiso and Tororo can forecast rains 1–2 weeks ahead. However at Jinja, the majority of farmers can forecast rains 3–4 weeks ahead.

Table 22.12. Percentage of farmers who use different temperature conditions to forecast onset of first rains

Category	Masindi		Wakiso		Jinja		Tororo	
	Early	Late	Early	Late	Early	Late	Early	Late
Temperature increase	20	8	22	7	31	16	18	9
Temperature decrease	2	15	7	7	8	11	6	6

Table 22.13. Monthly occurrence of temperature conditions described by farmers

Month	Masindi	Wakiso	Jinja	Tororo
December	26	0	5	13
January	51	17	23	20
February	66	51	40	78
March	46	20	16	55

Table 22.14. Percentage lead-time at which farmers forecast onset of first rains

Week	Masindi	Wakiso	Jinja	Tororo
1	43	15	8	18
2	30	43	11	18
3	3	3	10	3
4	8		28	

22.3.5.8

Current Use and Accuracy of the Rainfall Indicators

Even though there is a range of rainfall indicators, the majority of farmers use mainly 1–2 indicators. A few of them can use up to three rainfall indicators (Table 22.15)

Although the farmers use these indicators, they also experience conflicting results. As indicated in Table 22.16, between 25–56% of the farmers experience conflicting results from the forecasts made using the rainfall indicators.

The farmers' experience of conflicts in their forecasts could be an opportunity to build confidence in scientific rainfall forecasts since they also face the same problem.

22.3.5.9

Farmers' Needs for Meteorological Information

Although meteorologists have made considerable advances in producing climate forecasts, these products mainly provide information on rainfall levels for the season. This product is important to the farmers, however according to Table 22.17, knowing when the rains will start is the most important climate information needed by the farmers (end users).

The climate information needs of farmers should guide the approaches meteorologist should take to serve farmers better. At the moment the service clearly follows a top-down approach yet the recently recommended approach in rural development is bottom-up. In a bottom-up approach the end users are involved and are asked to spell out their information needs. It is also the current notion in rural development that to serve the rural people better, improvements are needed on what they know and do. Table 22.17 clearly indicates that among the sample population, farmer's primary concern is to know when to plant. Interestingly, they also want assistance in forecasting rainfall, which the meteorological services are well positioned to do.

Table 22.15. Percentage number of rainfall indicators used by farmers at a time

Number of indicators	Masindi	Wakiso	Jinja	Tororo
1	10	27	25	15
2	59	31	50	73
3	21	14	3	3
4	3	5	1	1
5		15	1	

Table 22.16. Percentage of farmers experiencing conflicting results in forecasting rains

Site	Yes	No
Masindi	25	70
Wakiso	31	58
Jinja	30	50
Torero	56	36

Table 22.17. Services demanded by farmers from meteorologists

Interest	%
Know the right planting time	36
Learn how to forecast rains	22
Advise on rainfall forecasts	14
Why changes in rainfall seasons	7
Using rainfall forecasts	3
Attend weather seminars	2
Why poor crop yields	2

22.4

Summary Findings for Wakiso Survey

The findings confirm that the first important climate information needed by the farmers is when the seasonal rains will start. For this purpose, farmers look for local atmospheric conditions such as temperatures and winds. With reference to this, two hypotheses were derived as described below:

- The direction and speed of winds provide signals as to when the wet season is likely to start.
- The increase in local temperatures during the dry season signals when the wet season is likely to start.

While the hypotheses above are based on farmer's knowledge, their validity can be statistically validated and improved, using the very methods of scientific climate forecasting. However statistical validation requires records of weather observation made objectively. As such based on the technology used at most weather station, analysis of wind direction and force, observations had a high subjective element in reading using the Beaufort scale. However temperatures are read from thermometers, hence these readings are very objective. Therefore statistical validation was based on temperatures.

22.5

Statistical Validation of Farmers' Knowledge

22.5.1

Onset Dates of 1st Wet Season

Analysis of onset dates for the 1st seasonal rains for each site, indicate that the average onset dates are 70, 64, 63, and 57 for Masindi, Namulonge, Jinja and Tororo respectively. However the rains may set in as early as mid month of February (Julian day 45) and as late as end of month of March (Table 22.18).

One of the hypotheses derived from the farmers' knowledge is, that increase of temperatures during a dry season signals the onset of first rains approximately within a

week's time. As such maximum temperatures during a dry season are related to the timing of onset of seasonal rains.

Figure 22.3 reveals the positive rise of the maximum temperatures for Masindi, Wakiso, Jinja and Tororo from the month of November to a higher value by end of February when the rains usually start. This confirms with the farmers experience of observing increase in temperatures as a signal to when the rains are about to start.

The relationship between the maximum temperatures and onset of rainfall can be used to develop models to forecast when the seasonal rains could start. This requires identifying the significant periods during the dry season when the relationship is strong.

22.5.2

Correlation of Rainfall Onset Dates with Maximum Temperatures

There is a statistical variation between the relationship of dry season maximum temperatures and onset dates. There are periods when the relationship is significantly strong and periods when the relationships are weak. To show the persistence of the relationship between the two variances for each times series (1991–2000, 1992–2001, 1993–2002 and 1994–2003) the different times series have been included in the graphs.

Figure 22.4a reveals that for Masindi the relationship between the maximum temperatures for months December up to February is positive with onset date of first rains. The pattern of the relationship is the same for all the three series. The strong positive

Table 22.18. Average onset dates for the first seasonal rains

	Masindi	Namulonge	Jinja	Tororo
Average	70	64	63	57
Std	12	12	12	10
Min	45	45	45	45
Max	92	84	84	70

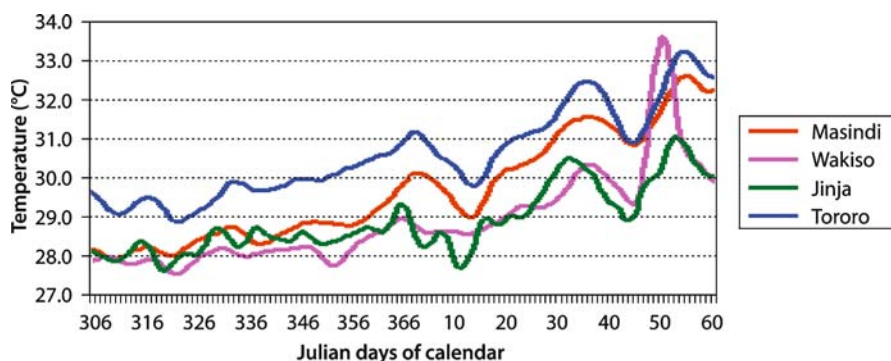


Fig. 22.3. Time series of 5-day average maximum temperatures for all sites based on data from 1989–2000 (December–January)

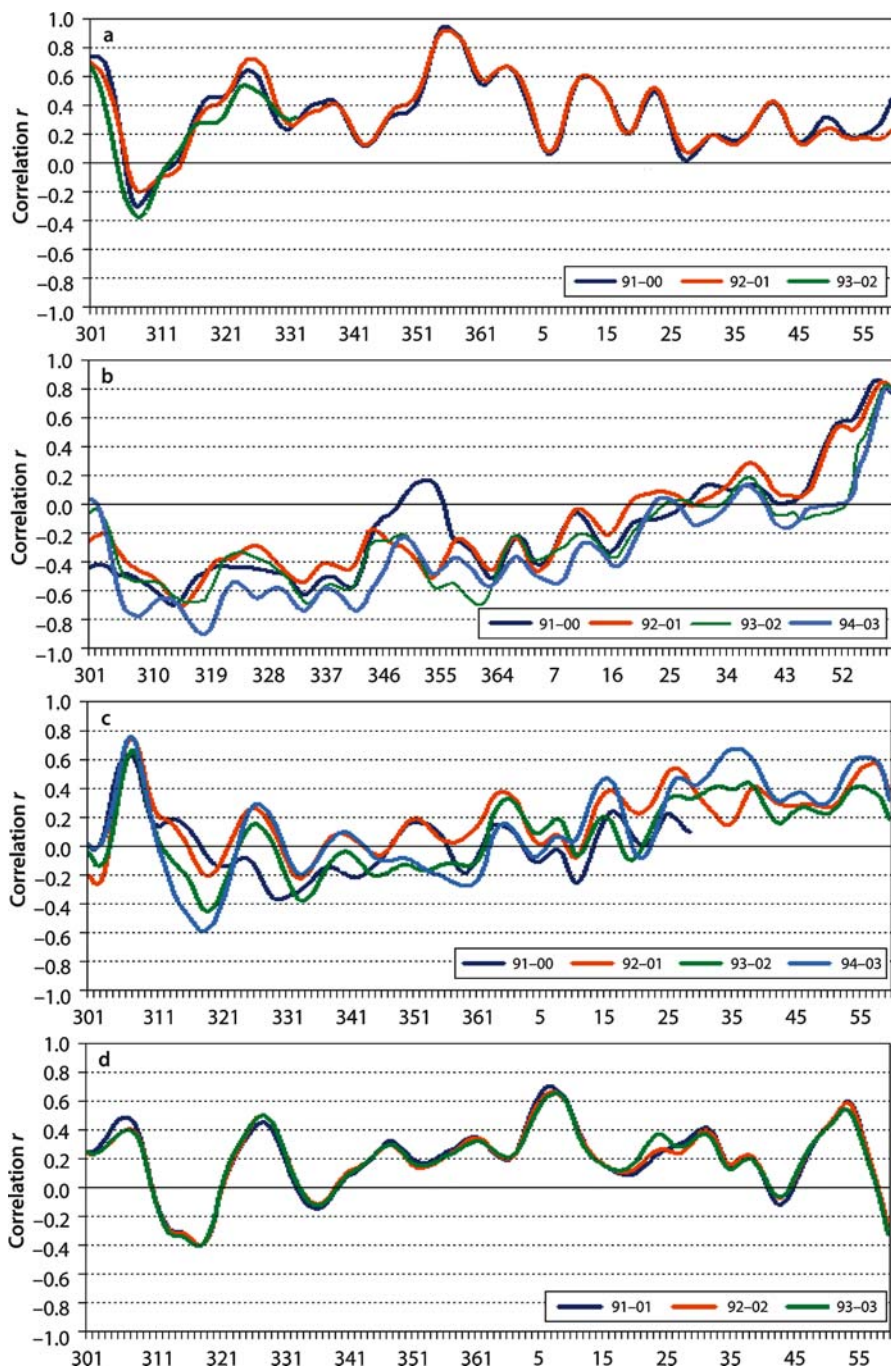


Fig. 22.4. Correlation values between maximum temperatures and rainfall onset dates for; a Masindi; b Namulonge; c Jinja; d Tororo

correlation is between the Julian days 354 and 360. The strongest correlation is $r = +0.93$ on day 356.

As for Namulonge the relationship during the month of November is negative, which gradually changes to a positive relationship by late February (Fig. 22.4b). A significant relationship is shown during the days 306 to 322 with particular highly strong negative relationship for Julian days 316–320.

Though the farmers can use the February temperatures to forecast the rains, another opportunity exists during the month of November. The strong relationship during this month suggests that the maximum temperatures for the month can be used to forecast the onset of 1st wet rains three months ahead.

In the case of Jinja, the relationship is generally negative during the months of December, which gradually changes to positive one by the end of February (Fig. 22.4c).

The onset dates based on a rain day threshold of 2.45 mm, show a relationship with maximum temperatures during the months of November to February. However during the month of November the relationship is negative, which gradually changes to a positive relationship by late February. A significant relationship is shown during the days 306 to 322 with particular highly strong negative relationship for Julian days 316–320.

At Tororo, the onset dates based on a rain day threshold of 2.45 mm, show a relationship with maximum temperatures during the months of November to February. The relationship is generally positive during the months of November and February (Fig. 22.4d). Significant relationship is shown during the 1st week of January with particular highly strong positive relationship for Julian day 5.

Though the farmers can use the February temperatures to forecast the rains, another opportunity exists at the beginning of the month of January. The strong relationship during this month suggests that the maximum temperatures for the month can be used to forecast the onset of 1st wet rains ahead of two months.

22.6

Regression Models Derived from the Relationships

22.6.1

Masindi District

Based on the rain day threshold of 2.45 mm, there is highly strong relationship ($r = +0.93$) between 5-day average maximum temperatures centered on Julian day 356 and onset dates for the first rains (Table 22.19).

A linear equation from this relationship was derived as ${}_{356}Y = 16.297x - 393.673$ (Fig. 22.5a) Using the 5-day average maximum temperatures centered on Julian day 356, the above equation could be used to forecast the onset date of the first rains 2 months ahead.

22.6.2

Wakiso District

The relationship of average maximum temperatures and onset dates based on rain day threshold of 2.45 mm is highly strong centered on Julian day 319. The correlation value

Table 22.19. Details of regression models derived for different survey sites

	Massindi	Namulonge	Jinja	Tororo
Linear Model Estimation				
Multiple R	0.932	0.909	0.751	0.723
R Square	0.869	0.827	0.563	0.523
Adjusted R Square	0.853	0.805	0.509	0.463
Standard Error	7.232	4.285	8.926	7.452
Analysis of Variance				
Regression				
DF	1	1	1	1
Sum of Squares	2773.15	701.48	822.72	487.278
Mean Square	2773.15	701.48	822.72	487.278
F value	53.02	38.20	10.32	8.773
SignF	0.0001	0.0003	0.0124	0.0181
Residuals				
DF	8	8	8	8
Sum of Squares	418.45	146.92	637.28	444.322
Mean Square	52.31	18.36	79.672	55.54
F value				
SignF				
Variables in the Equation				
Julian Day	356	319	307	7
B	16.30	-10.43	13.994	3.889
SE B	2.24	1.69	4.36	1.31
Beta	0.93	-0.91	0.75	0.72
T	7.28	-6.18	3.21	2.96
Sign T	0.0001	0.0003	0.0124	0.018
Constant				
B	-393.67	353.12	-328.12	-62.967
SE B	64.44	46.70	121.84	40.64
Beta				
T	-6.11	7.56	-2.69	-1.55
Sign T	0.0003	0.0001	0.0274	0.16

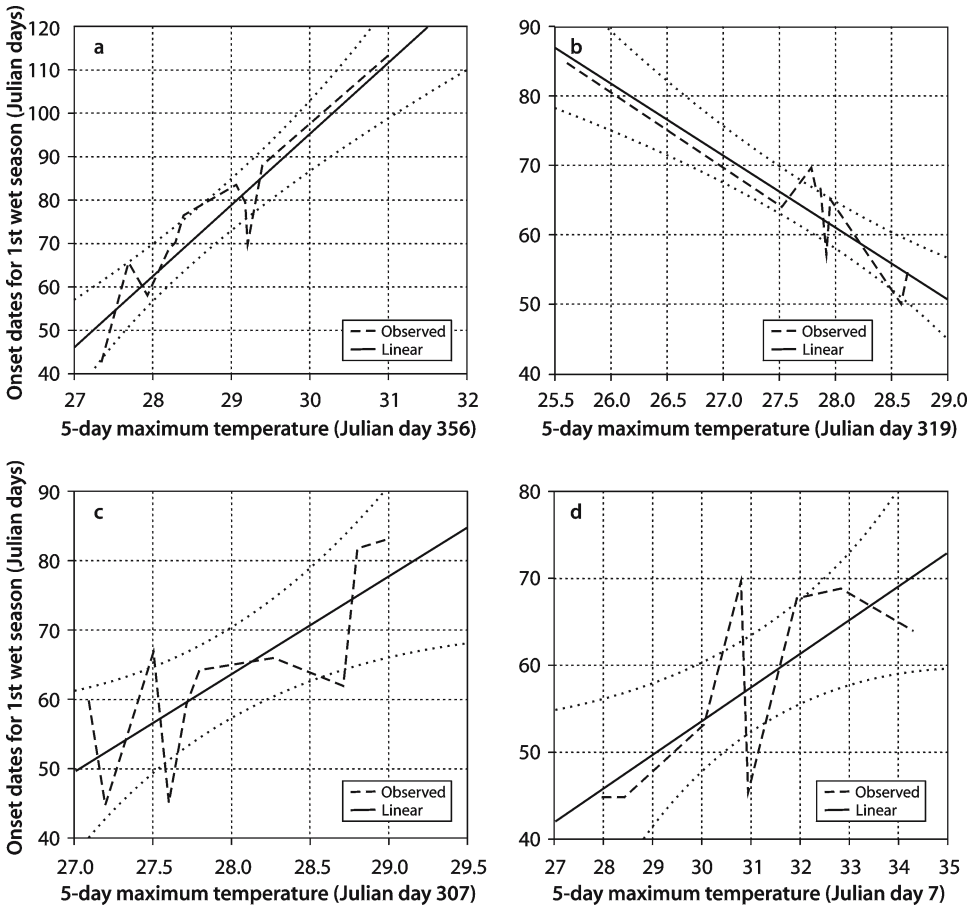


Fig. 22.5. Linear forecasting models for; a Masindi; b Namulonge; c Jinja; d Tororo (temperature data in °C)

of the relationship is $r = -0.91$ (Table 22.19). From this relationship, a forecasting model was derived as shown in Fig. 22.5b.

The linear equation derived from the graph in Fig. 22.5b is ${}_{319}y = -0.425x + 353.115$.

The predicted onset date based on 5-day average maximum temperatures was centered on Julian day 319. Using this forecasting model, the start date of the first rains can be forecasted 3 months ahead.

22.6.3 Jinja District

Based on the rain day threshold of 4.95 mm, there is highly strong relationship ($r = +0.75$) between 5-day average maximum temperatures centered on Julian day 307 and first rains onset dates (Table 22.19).

A linear equation from the relationship above was derived $_{307}y = 12.149x - 274.021$ (Fig. 22.5c). Using the 5-day average maximum temperatures centered on Julian day 307, the above equation could be used to forecast the onset date of the first rains ahead of 3 months.

22.6.4 Tororo District

The relationship of average maximum temperatures and onset dates based on rain day threshold of 2.45 mm is highly strong centered on Julian day 7. The correlation value of the relationship is $r = +0.72$ (Table 22.19). From this relationship, a forecasting model was derived as shown in Fig. 22.5d.

The linear equation derived from the graph in Fig. 22.5d is $_{7}y = 3.889x - 62.967$. While $_{7}y$ represents a predicted on set date based on 5-day average maximum temperatures centered on Julian day 7. Using this forecasting model, the start date of the first rains can be forecasted months ahead.

22.7 Discussion

The above results indicate common linkages between indigenous and scientific knowledge systems on climate observation. In either knowledge systems, there is practice of observing the atmospheric environment for the purpose of forecasting weather and climatic events. The practice of farmers suggests a strong need for climate forecasts to solve their agricultural production problems. Such findings are in line with studies by Roncoli et al. (2001) and Onyewotu (2000).

22.7.1 Weather and Climate Knowledge Systems

Although there are common linkages in both the climate knowledge systems, there are also noted differences among them. These differences are centered on the range and interval of observations, documentation, and forecasting methods. While the farmers have a holistic observation of the local environment indicators they observe, the meteorologists have selective but larger geographic observations. For example among the range of environmental indicators farmers observe, the scientists observe only temperatures, winds, clouds and precipitation. Meteorologists also have a set time interval to make the observations. The documentation system is another point of concern. Though the farmers observe a wide range of environment indicators, their observations are mainly recorded in their memory. However scientists keep historical records of the observations for deeper study. The results revealed that farmers are able to forecast the first rains easier than the second wet season. This is an interesting issue because scientists forecast the second rains easier than the first rains. The differences highlighted above indicate the opportunities meteorologists can use to develop better forecasts.

22.7.2

Outputs from Knowledge-Sharing

The common and different practices of observing environmental indicators by both farmers and meteorologists, for the purpose of forecasting seasonal rains form a good platform to produce needed climate information for end users. Through this study the farmers' indigenous climate practices, knowledge gaps, and farmers priority climate information needs are revealed. The scientific reasons for the ability of farmers to forecast the first rains better than the second rains need investigation. However suggestions may include the following. Farmers regard the first rains as the major rainfall season, when they produce most crops. As such there is always a lot of agriculture planning and production expectations. Secondly the dry season following the first rains is pronounced and longer than the dry season following the second rains. Therefore during the pronounced and longer dry season, rainfall indicators become well established for the farmers to easily relate them with seasonal rains. Steady winds in Uganda (Jameson 1970) are experienced at the height of the dry season in February. Thirdly, the variability of the first rains may be less than the second rains enabling farmers to master its developments. The influence of climate change to differences in degree of variability of both wet seasons could also be investigated.

Meteorologists forecast the second rains in Uganda easier than the first rains probably due to the following. The statistical models used by meteorologists are produced from global climate circulatory system, which are more pronounced during the second part of the year. Additionally the models are developed to detect extremes from the normal conditions. Therefore the forecasting models are more efficient to forecast the second rains, which are more variable than the first rains.

22.7.3

Farmers' Use of Local Forecasts

Although a basic seasonal rainfall forecast should indicate the onset time, rainfall amount and duration of the expected season, results from this study indicate that the majority of farmers use the environment indicators to forecast onset while the meteorologist basically forecast rainfall amount. Harmonizing the two climate forecasts could provide a better climate information package for the farmers. Interestingly, whereas the farmers can forecast the onset of first rains wet season with a lag period, additional results indicate that the majority of them wait for the rains to actually start to determine the right planting time. They wait for the rains to continue for at least 2–3 days. Others wait to experience the rains in the traditional planting calendar months of March. There could be various reasons for this scenario of which may include the following. First the lag period between when the farmers can use the indicators to forecast the onset of the rains and when the rains actually do happen is very short. For example use of increasing ambient night temperatures as signal that seasonal rains are about to start gives a short period. The correlation graphs of maximum temperatures and onset dates confirm this with strong relationships at the end of February when the season usually begins. Secondly although the farmers can forecast the onset

of the rains, during the dry season the land is dry and hard to cultivate. So farmers wait for the rains to wet the soils to plough and plant. The third reason could be that although they can forecast the rains, but due to the increasing irregularity of seasonal rains, and climate change they may not be confident with their forecasts. Hence they wait for the rains to start then they plant.

22.8

Conclusions

The above study reveals, the common practices that farmers and meteorologist use in observing atmospheric conditions in pursuit of forecasting seasonal rains for crop production. There are differences in the way both farmers and meteorologists observe and develop climate scenarios that each group can forecast. The farmer's practice of forecasting rains using their rainfall indicators highlights the importance of climate forecasts to them to ensure food security. The challenges farmers experience in producing and using climate forecasts is a development activity which is very critical to be addressed by the meteorologists. Through studying the indigenous climate knowledge systems, meteorologists can identify the priority climate information needed by farmers. Considering the farmer's priority climate information needs, and interest in improving their own local forecasts, a new paradigm of work from meteorologists is needed (Engel 1997) learning to incorporate the multiple rationalities of stakeholders, rather than promoting linear, exclusive and one-dimensional ways of thinking.

Donnelly (1998) points out that recent developments focus on capacity and institutional building. Since farmers use their indigenous knowledge at the local level as the basis for decisions pertaining to food security, understanding the farmers practice in forecasting seasonal rains may help meteorologists improve their services to the end users. As such building on indigenous knowledge (Gorjestani 2000) can be particularly effective in helping to reach the poor since indigenous knowledge is often the only asset they control, and certainly one with which they are very familiar. The development of forecasting models from this study confirms with the extension approach of helping farmers based on what they have and know.

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Appendix

Table A22.1 Local names of temperatures conditions in Masindi

Rank	Name	%
1	Obutagasi	48
2	Omurombwe	28
3	Embeho	8
4	Akanyango	2

Table A22.2 Local names of temperatures conditions in Namulonge

Rank	Name	%
1	Ebugumu	44
2	Obutiti	7
3	Okubugujja	3
4	Kikome	3
5	Omututulu	2
6	Kyeya	2
7	Okubindabinda	2
8	Luwewowewo	2
9	Embuyaga	2
10	Empewo	2
11	Olufu	2
12	Kasambula	2

Table A22.3 Local names of temperatures conditions in Jinja

Rank	Name	%
1	Lubugumu	4
2	Lwota	3
3	Nsaikya	3
4	Luwewowewo	3
5	Kasanaka	1

Table A22.4 Local names of temperatures conditions in Tororo

Rank	Name	%
1	Ngicho	29
2	Leitho	28
3	Mulengela	11
4	Kadis (Kidisa)	9
5	Nongino	8
6	Kothodisa	3

Improving Applications in Agriculture of ENSO-Based Seasonal Rainfall Forecasts Considering Atlantic Ocean Surface Temperatures

G. O. Magrin · M. I. Travasso · W. E. Baethgen · R. T. Boca

23.1

Introduction

Climate uncertainties, derived from annual climatic variability, often lead to conservative crop management strategies that sacrifice some productivity to reduce the risk of losses in bad years. The availability of ENSO-based climate forecasts has led many to believe that such forecasts may benefit decision-making in agriculture. The forecasting capability may allow the mitigation of negative effects of ENSO-related climate variability as well as taking advantage of favorable conditions (Stern and Easterling 1999).

Benefits of using ENSO-based climate forecasts have been demonstrated in South America. Changing crop mix (Messina et al. 1999) or crop management options were proposed as adaptive measures to cope with climatic variability (Magrin et al. 2000; Jones et al. 2000). However, the large inconsistency of the precipitation signal within ENSO phases led to considerable overlap in yields and net returns for the various ENSO phases (Ferreira et al. 2001), decreasing the potential usefulness of the forecasts (Magrin and Travasso 2001; Podestá et al. 2002).

But ENSO is not the unique source of climatic variability in southeastern South America. Evidence of the influence of South Atlantic Ocean (SAO) on precipitation was presented for Uruguay and south Brazil by Díaz et al. (1998). Barros et al. (2000) signaled the influence of the South Atlantic Convergence Zone (SACZ) on midsummer interannual variability of the low-level circulation and precipitation in subtropical South America. Recently Berri and Bertossa (2004) reported that the Atlantic Ocean influences seasonal precipitation over the northwestern and southeastern parts of southern central South America.

Furthermore, in previous works significant relationships were found between SAO SST anomalies and crop yields or precipitation anomalies in the Pampas region of Argentina. In comparison to ENSO or SSTs from the Pacific, SAO SSTs presented a stronger signal on crop yields in the southern part of the region, especially for maize (Travasso et al. 2003a,b).

These antecedents encourage the consideration of SAO SST anomalies as a way to improve climate forecasting and decision-making in agriculture.

The aim of the present work was to explore the capability of considering SAO by itself and in conjunction with ENSO phases to optimize maize agronomic management practices and, to assess the additional economic value of including SAO information in an ENSO-based seasonal forecast.

23.2 Methods

A location placed in the southeastern part of the Argentina's Pampas region, Azul (latitude 36.8° S, long 59.9° W), was selected as case study. Daily climatic data for maximum and minimum temperature, precipitation and solar radiation were available since 1931 from the National Meteorological Service.

CERES-Maize model included in DSSAT v3.5 (Tsuji et al. 1994) was used to examine the benefits of tailoring crop production decisions to different types of climate forecasts. The model had been previously calibrated and validated in the region with estimation errors for yield predictions lower than 10% at the field level (Travasso and Magrin 2001).

Different types of climate forecasts were used based on: (a) ENSO phases (neutral, El Niño and La Niña) following the Japan Meteorological Agency classification, (b) three monthly (November-December-January) rainfall categories, and (c) South Atlantic Ocean SST anomalies (SAO).

Smoothing techniques (Cleveland et al. 1988) were used for isolating the low frequency variability in monthly precipitation record. Then, the anomalies (difference between observed and smoothed values) were classified in terciles obtaining three rainfall categories: wet (upper tercile), normal and dry (lower tercile).

South Atlantic Ocean SST anomalies (SAO) (0–20° S, 30° W–10° E) were obtained from the NOAA website. SAO values corresponding to August and September, which are significantly related to maize yield in this location (Travasso et al. 2003a) were used. SAO anomalies were classified in quartiles and 3 categories were used: warm (wSAO = upper quartile), neutral (between probability of 75 and 25%) and cold (cSAO = lower quartile).

Model runs were done for the period 1931–2002 considering the soil series predominant for Azul (Typic Argiudoll) and the most frequent farm management: planting on 30 October with a plant density of 7 plants m⁻², and a nitrogen fertilizer rate of 60 kg N ha⁻¹. These runs were taken as the baseline data and corresponded to expected yields when climate forecast is not considered. The crop's gross margin was calculated according to the prices presented in Table 23.1.

Optimal management options for each climate forecast method were obtained by varying planting dates (15-day intervals starting at 15 October) and nitrogen doses (0, 20, 40, 60, 80, 100, 120 kg N ha⁻¹). The best option for each extreme phase (El Niño, La Niña, wet, dry, wSAO and cSAO) was defined as the one producing the highest gross margin. For the years classified as neutral or normal the management practices were always the same (typical farm management) assuming that those years, farmers would not use climate forecasts in their decision-making.

The economic value of climate forecast was calculated as the difference in gross margin between the best management option for each forecast and the typical management without considering forecast.

23.3 Results

The cumulative probability for grain yields under the typical farmer management for the different climate predictions methods (precipitation terciles, ENSO, and SAO

Table 23.1. Prices considered for gross margin calculation

Item	Price (U.S.\$)
Labour	69 ha ⁻¹
Fertilizer application	12 ha ⁻¹
Seed	57 ha ⁻¹
Herbicide	34 ha ⁻¹
Insecticide	1 ha ⁻¹
Fertilizer (urea)	0.34 kg ⁻¹
Fertilizer (diammonium phosphate)	0.35 kg ⁻¹
Harvest	8%
Commercialization	27%
Maize price (April 2005)	77 t ⁻¹

anomalies) are presented in Fig. 23.1. The best method allowing to discriminate among yield categories was “precipitation terciles” (i.e. assuming a “perfect” forecast). The use of “ENSO phases” was useful only in 50% of the years, while “SAO anomalies” clearly separated the highest yields.

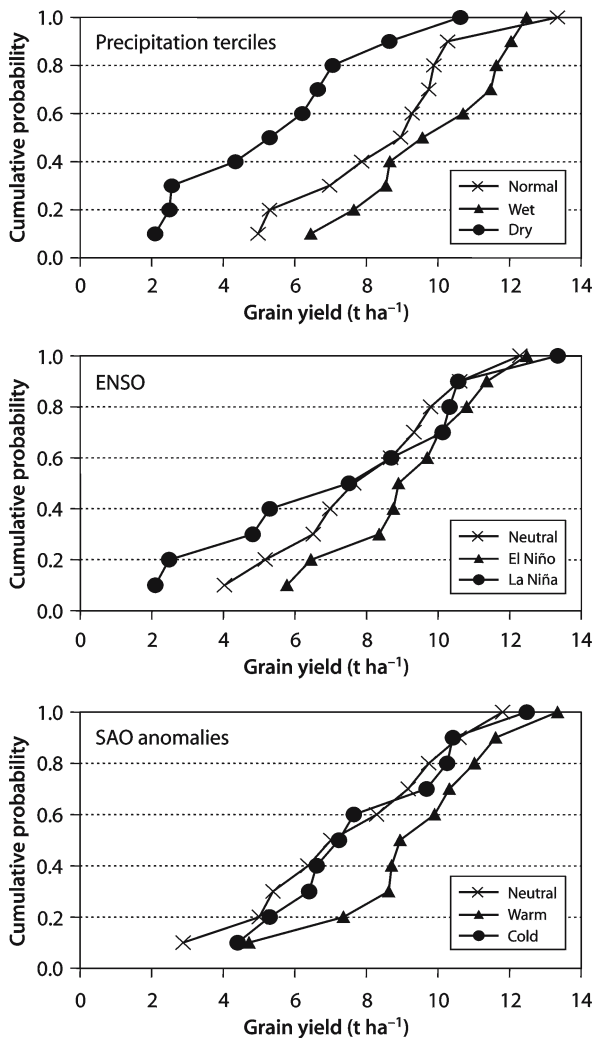
This result suggests that maize yields are likely to be driven not only by the influence of ENSO phases but also by South Atlantic Ocean conditions. Figure 23.2 shows the relationship between maize yields and SAO temperature anomalies. Upper quartile SAO anomalies were consistently associated with mean or high yield levels, with only one exception. It is important to emphasize that our results suggest that even under La Niña or neutral years, high or normal maize yields could be expected if SAO anomalies in August and September are higher than normal. However, with normal or low SAO anomalies yield behavior was erratic.

ENSO phases were combined with SAO anomalies in an attempt to improve yield predictions. In Fig. 23.3 maize yields were regrouped as La Niña (all La Niña years except those with warm SAO anomalies), neutral (all neutral years except those with warm SAO anomalies) and a third group including El Niño years plus warm SAO years. Because this combination seems to be a better approach to separate yields categories, we decided to consider it as a fourth climate forecasting method.

Optimal management options, grain yields and gross margins for each one of the considered climate forecast are summarized in Table 23.2. Expected yields in Azul averaged 7.70, 8.48, 8.18, 8.02 and 8.39 t ha⁻¹ for most common farmer management and management optimized by rainfall terciles, ENSO, SAO and ENSO + wSAO, respectively. For gross margin these figures were 140, 172, 155, 147, and 162 U.S.\$ ha⁻¹.

Optimal crop management options for less favorable years (La Niña, Dry) resulted in later planting dates and lower N rates. For more favorable years (El Niño, Wet and wSAO) higher N rates was a better option, although the optimal planting date differed among methods (Table 23.2). These differences in optimal crop management evidenced between El Niño and Warm SAO could be attributed to differences in their signal on precipitation. During El Niño years rainfall tends to be higher than normal in November-December (Barros et al. 1996; Magrin et al. 1998), while Warm SAO episodes are

Fig. 23.1. Cumulative probability for simulated grain yields for each weather category



positively correlated with October–February precipitations (Travasso et al. 2003b). Because maize crops are highly sensitive to water shortage during the pre-flowering period, for planting dates in mid October (like in El Niño years) water availability will be crucial during December, but late planting dates (wSAO) will be more dependant on January rainfall. As shown in Fig. 23.4 precipitation anomalies in Azul tended to be higher in January during the wSAO years.

The economic value (*EV*) of forecast (Table 23.3) was obviously the best when considering precipitation terciles (22.9%). The *EV* for individual ENSO phases (10.5%) or SAO anomalies (5%) was considerably lower. However using ENSO forecast and taking into account warm SAO anomalies during August and September could signifi-

Fig. 23.2. Relationship between simulated maize yield and South Atlantic Ocean surface temperature anomalies

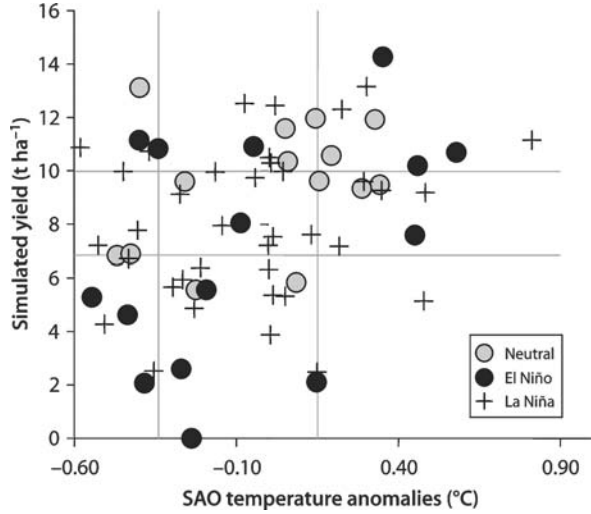
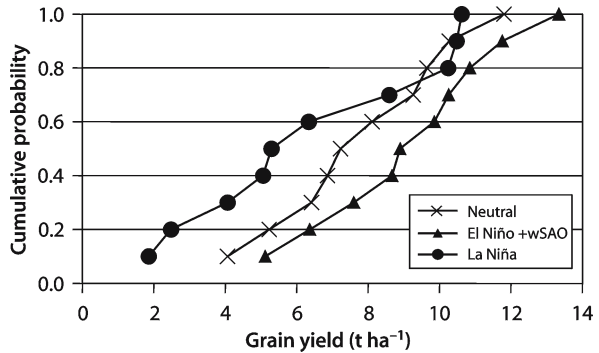


Fig. 23.3. Cumulative probability for simulated grain yields for ENSO + warm SAO forecast



cantly increase the incomes (15.9%). It is important to note that in dry years the *EV* attained 90% while in the wet years it ranged between 15 and 30% (Fig. 23.5).

Variability in precipitation within an ENSO phase is one of the most important obstacles for forecast’s adoption. For example, if dry conditions are expected during a given ENSO event but do not materialize (as happened in 1999–2000 in the western Pampas), cold events will not appear to be very salient or memorable. (Podestá et al. 2002). In this particular year, classified as La Niña according to Pacific conditions, SAO temperatures were significantly higher than normal and, as mentioned above, warm SAO is associated with positive rain/yield anomalies in the southern Pampas. Precipitation in December, January and February in Azul was 25.0, 9.0 and 134.0 mm over the mean values.

Therefore combining both approaches (ENSO + SAO) could be promising for improving the applications of ENSO-based seasonal forecasts in agriculture.

Table 23.2. Optimal management options and expected outcomes for different climate forecasts

Years	<i>n</i>	Planting date	Total N applied (kg ha ⁻¹)	Predicted yield (t ha ⁻¹)	Predicted margin (US\$ha ⁻¹)
All years (according to most frequent farmer management)					
All	68	30 October	60	7.70	140
Optimized by three monthly precipitation terciles (November to January)					
Wet	16	15 October	120	11.66	294
Normal	35	30 October	60	8.11	160
Dry	17	30 November	40	6.23	81
Mean				8.48	172
Optimized by ENSO phase					
El Niño	14	15 October	120	10.31	226
Neutral	39	30 October	60	7.63	136
La Niña	15	15 November	60	7.63	136
Mean				8.18	155
Optimized by SAO temperature anomalies					
Warm	20	15 November	80	9.62	221
Neutral	32	30 October	60	7.09	109
Cold	16	30 October	80	7.88	132
Mean				8.02	147
Optimized by ENSO phase and SAO temperature anomalies					
El Niño	14	15 October	120	10.31	226
Warm SAO	14	15 November	80	9.65	223
Neutral	30	30 October	60	7.42	126
La Niña	10	15 November	60	6.85	97
Mean				8.39	162

SAO = South Atlantik Ocean.

Table 23.3. Absolute and relative value of optimal use of various types of perfect seasonal forecast for maize management in Azul

Forecast value	Rain terciles	ENSO phases	SAO anomalies	ENSO + SAO
Absolute (U.S.\$ ha ⁻¹)	31.9	14.7	7.0	22.2
Relative (%)	22.9	10.5	5.0	15.9

Fig. 23.4. Precipitation anomalies during December, January and February for; **a** El Niño years; **b** warm SAO years

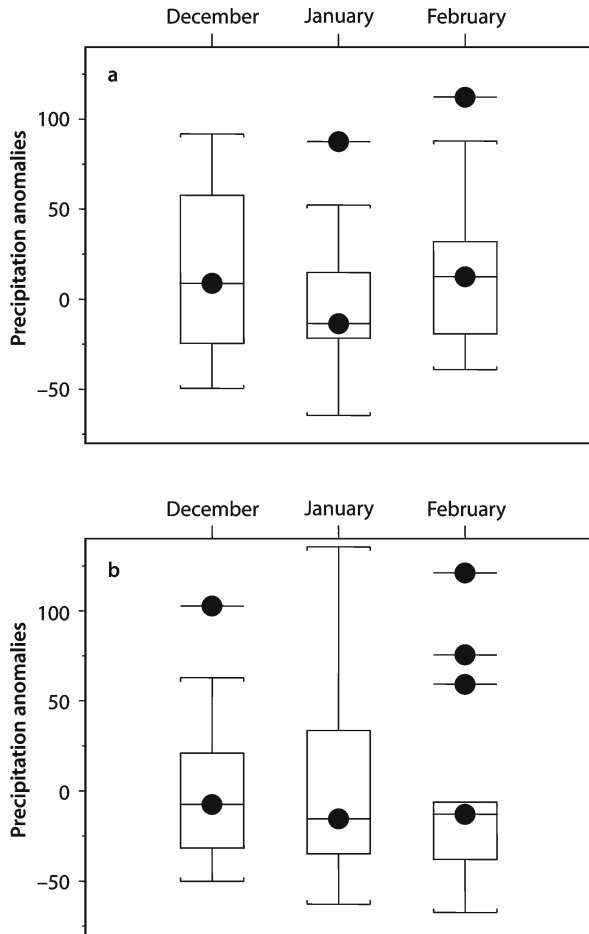
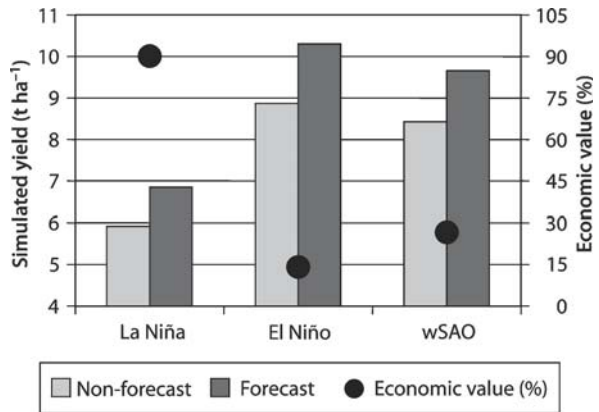


Fig. 23.5. Predicted yields and economic value of ENSO-SAO climate forecast



23.4

Conclusions

Upper quartile SAO anomalies in August and September were consistently associated with mean or high maize yield levels, even under La Niña or neutral years. Complementing ENSO phases with wSAO led to increase the economic value of ENSO-based climate forecast by 5.4%.

Differences in optimal planting date between El Niño and wSAO years can be attributed to differences in rainfall distribution. Results obtained could contribute to improve the applications of ENSO-based seasonal forecasts.

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AGRIDEMA: An EU-Funded Effort to Promote the Use of Climate and Crop Simulation Models in Agricultural Decision-Making

A. Utset · J. Eitzinger · V. Alexandrov

24.1 Introduction

Global climate change will lead to shifts in climate behavior and could cause severe impacts on ecosystems in the next decades (IPCC 2001). In particular, climate change will have significant effects on agricultural production. Negative climate-change impacts on agriculture could be avoided or reduced significantly by taking appropriate decisions, which can be based on the available crop-growth simulation models, as well as on forecasts and climate scenarios (Adams et al. 1998; Hoogenboom 2000).

There are several climate modeling tools currently available. For the long-term (decades) assessments, global circulation models (GCMs) compute several scenarios of the future climate behavior, which have been considered adequate, although those scenarios must be downscaled to smaller areas for practical applications. For short-term, seasonal-forecasts according to El Niño-Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO) behaviors, as well as other sources of climate variability, are also available (Doblas-Reyes et al. 2006). These scenarios and forecasts can be downscaled by weather generators, regional climate models and other methods, to reflect local climatic conditions (Wilby and Wigley 2001). Besides, mechanistic crop-growth simulation models can effectively estimate crop yields, as well as yield risk, under any climate conditions (Hoogenboom 2000).

There are many reports of agricultural global-change impact-assessments based on simulation modeling. Tubiello and Ewert (2002) summarize more than 100 such assessments, made worldwide. Likewise, Alexandrov (2002) provided a large review of model applications in Europe. However, most of those research results remain still as theoretical assessments and they have not led to successful agricultural decision-making applications.

The producers of climate-forecasts, downscaling techniques and crop-growth models are often not aware about the actual needs of small and medium agricultural enterprises and they may not know what mitigation strategies these farmers can undertake to adapt to global climate change consequences. Moreover, the reliable agricultural decisions depend on many local issues that are beyond the higher level researcher context. On the other hand, farmers usually do not know how to interpret the management implications of presently-available climate forecasts, usually written in a probabilistic language.

Nevertheless, current research results on climate-change impacts on agriculture can be relatively easily introduced for local decision-making, if the relevant institutions and people are involved. Likewise, as pointed out by Hansen (2002), engaging relevant institutions in all phases of agricultural climate-impact assessments is crucial for the

long-term success of these assessments. For example, the significant climate-forecast applications in agricultural decision-making, as done in Australia (Hammer et al. 2001) and in the U.S. (Jagtap et al. 2002), have been achieved only by the joint effort of high-level researchers and technicians from agricultural extension services (Meinke et al. 2001; Hansen 2002).

Experts and researchers at well-known research centers in Europe and other places (referred hereafter as “developers”) have established a significant know-how and produced relevant tools for such climate-impacts studies. But practical experts at local agricultural research centers as well as agricultural advisers (referred hereafter as “users”) who should apply these tools for agricultural decision-making, are often not aware about the availability of such tools or their access to such tools is quite limited due to several reasons, as financial issues or lack of user-friendly design of tools.

A connection is needed between the “developers” and “users”, to improve decision-making by better implementing this know-how and model tools. Furthermore, feedback from the end-users to the developers is a prerequisite for improving these tools for their practical use e.g. by providing background information, setting up the actual input data needs, fitting time and spatial scales as required by specific applications and other similar issues.

In that context AGRIDEMA, a new Specific Support Action (SSA), has been funded by the EU Sixth Framework Program from January 2005 to June 2007. AGRIDEMA comprises researchers from Spain, Austria and Bulgaria. The SSA aims to promote a research network, linking European developers with the potential users of their research results.

Mediterranean countries could face the highest negative consequences of global warming within Europe, through water-shortage and crop-water requirements increments (Olesen and Bindi 2002). Besides, since climate-change and extreme events effects could be more serious in countries with less-developed agriculture (IPCC 2001), the EU associated countries from central and eastern Europe, with relative reduced technological capacities, would be more affected than northern-European countries. Therefore, AGRIDEMA will focus on southern, central and eastern Europe, as well as on the countries of the Mediterranean area.

24.2

AGRIDEMA Description

AGRIDEMA comprises the following specific objectives:

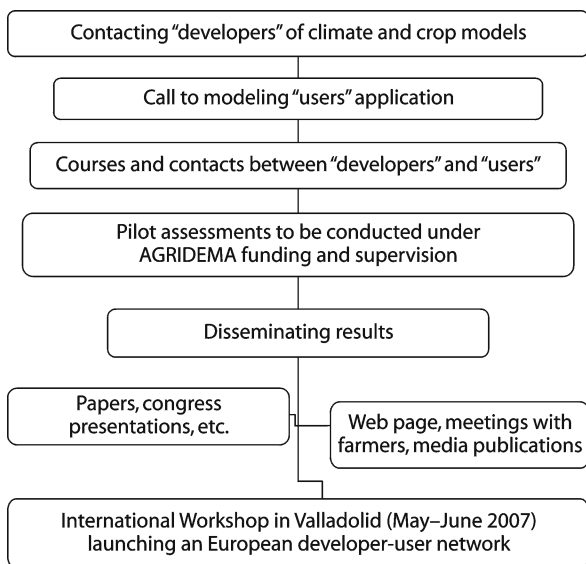
1. To identify European experts who developed, improved and tested simulating tools such as GCMs, seasonal forecasts, regional downscaling techniques and agricultural-impact simulation models and invite them to participate in the SSA proposal activities for implementing their tools and know-how.
2. To identify and undertake appropriate SSA activities with potential users of the modeling tools. They must be related to agricultural decision-making and to climate-risk assessments and located in central, eastern and southern Europe, as well as in the countries of the Mediterranean area. These users will learn and become familiar with the techniques, their needs for applying these tools will be identified and feedback will be provided to the developers.

3. To conduct short courses, where the invited developers will present the important aspects of their developed or validated tools to the invited users coming from central, eastern and southern Europe, as well as from the Mediterranean countries.
4. To perform pilot collaborations between developers and users from central, eastern and southern Europe, as well as from the Mediterranean countries, under the supervision of the SSA. Direct collaborations, out of SSA consortium supervision, would be welcome as well.
5. To disseminate the results obtained and to build up a wider consortium, comprising both, the developers of the simulating tools and the potential users of such tools (e.g. experts from regional agricultural-oriented research centers, advisers and farmers).

According to these objectives, several tasks or “work packages” were included in AGRIDEMA. The tasks can be seen in Fig. 24.1 and several reports have been scheduled as well. Three of these reports will be in public domain and will refer to the “State of Art” of climate and crop-growth modeling tools concerning their practical applications to agricultural decision-making, under climate change conditions.

As can be seen from the AGRIDEMA specific objectives and the corresponding tasks, contacts will be made with developers of both climate and crop-growth modeling tools. Invitations to join AGRIDEMA will be sent to well known European centers, where GCM outputs, seasonal forecasts, downscaling techniques and crop-growth simulation models are available. As a result of these contacts, short-courses and demonstrations will be arranged with those developers interested in applying their developed tools. AGRIDEMA would bring to model developers a good opportunity to introduce their models in a wide community of potential users. A final report comprising all the final agreements with developers will be written by the SSA partners.

Fig. 24.1. AGRIDEMA work packages and general schedule



An AGRIDEMA participation call will be launched among the potential users. Since there is a geographical complementarity between the participating institutions, the Spanish Coordinator will seek possible participants for SSA-activities from southern Europe and the Mediterranean countries, whereas the Austrian and Bulgarian partners will do the same concerning the potential participants from central and eastern Europe, respectively.

The requisites of expected AGRIDEMA users are:

- a To be able to communicate in English and to be able to work with data management software (Windows, Excel, etc.).
- b To be involved with local agricultural decision-making, advising and farming in the regions of southeast, southwest and middle Europe including non-European Mediterranean countries.
- c To be aware of the potential benefits of agricultural decision modeling tools, be able to identify which agricultural management options should be change and how to optimize management and reduce climate risks in local agricultural production.
- d To make available data for the training course and for the potential SSA pilot assessments (crop growth and yields, meteorological variables, soil properties, irrigation and crop management scheduling, etc.).

Additionally, users conducting PhD studies in the same subjects of AGRIDEMA activities will receive a special consideration for participating in the project.

The AGRIDEMA partners must write a final report about their effort in contacting the users. The report will point out which users were finally selected and why. Since this would be probably the first European attempt for encompassing developers and users, concerning agricultural climate-change impact assessments, the report will serve as a guide for future efforts in identifying potential users of the European tools available for such assessments.

Several users will be selected among the course participants in order to conduct "pilot assessments". The content, objectives, goals of the pilot assessments have to be judged by the SSA partners under the agreement of the developers and users. The content of the pilot assessment should cover the topic of the AGRIDEMA project and to be problem-oriented. Assessments addressed to evaluate extreme-event risks in agriculture, using the climate and crop-growth modeling tools, are particularly encouraged. The AGRIDEMA pilot assessments should evaluate irrigation, land use or crop-management options under local conditions, which could be useful (or not) in case of climate risks. Furthermore, pilot assessments will point out the advantages or constraints of the modeling tools applied, the improvement needed as well as potential benefits of the results obtained for agricultural decision-making.

The results obtained through AGRIDEMA should be disseminated as much as possible. An SSA-related web will be created, where the results obtained will be posted to provide access to the international audience and a discussion forum will be opened through the web, promoting contacts between developers and users in the framework of a European network.

AGRIDEMA comprises also an international workshop, to be held in Spain, where the SSA results will be presented. All the institutions directly involved in the SSA activities will participate in the workshop. Furthermore, other relevant institutions in-

volved in developing agricultural decision-making under global-change conditions will be invited to attend the workshop. A European network, concerning the development and regular use of modeling tools, as a way to provide successful agricultural decision-making under global-change conditions, will be launched during the workshop. The state-of-the-art research will be presented in the workshop and priorities for future research will be identified.

Through the network modeling tools in agricultural decision-making will be introduced to a wide non-scientific but stakeholder audience. The goal is to show to these institutions and associations how the modeling tools can help in taking appropriate decisions to mitigate the agricultural climate-risks.

24.3

AGRIDEMA Current Status

According to the AGRIDEMA timetable, the partners are involved in their first task, i.e. contacting developers, although some users have already been contacted. Several developers or sponsors of remarkable climate and crop-growth modeling tools have been already contacted. Many of them participated in AGRIDEMA activities and gave lectures in the courses held in Vienna, from 21 November to 2 December 2005. Positive answers to AGRIDEMA invitations have been received from the DEMETER multi-model ensemble (Doblas-Reyes et al. 2006); the LARS-WG weather generator (Semenov and Barrow 2002) and the WOFOST crop-growth model (Van Ittersum et al. 2003) groups; among others. Besides, European sponsors of DSSAT (Jones et al. 2003) and CROPSYST (Stockle et al. 2003) models were in Vienna. Several other climate and crop-growth model developers are scheduled to be contacted. The final list of developers participating in AGRIDEMA activities is now ready.

Potential user institutions interested in attending the AGRIDEMA courses and eventually conduct “pilot assessments” have been identified. Institutions from Spain, Italy, Greece, Morocco and Egypt are already being evaluated as potential AGRIDEMA users.

Despite the possibility of being directly involved in AGRIDEMA activities from both developer and user sides, the SSA partners encourage all the potentially interested people to contact us. AGRIDEMA is an attempt to reduce the gap between people involved in climate and crop-growth modeling efforts and their potential users. It is a right step to make available the current modeling tools to assist in local agricultural decision-making, which is consistent with the CLIMAG goals.

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Web-Based System to True-Forecast Disease Epidemics – Case Study for Fusarium Head Blight of Wheat

J. M. C. Fernandes · E. M. Del Ponte · W. Pavan · G. R. Cunha

25.1

Introduction

Disease forecasting has become an established component of quantitative epidemiology. The mathematics of disease dynamics is the core of several disease forecast models that have been developed in the last four decades. However, many models have not lived up to the expectations that they would play a major role and lead to a better disease management. Amongst the reasons, the presumption of a disease forecast model is that it makes projections of major events in disease development and most present forecast models do not (Seem 2001). An exciting development in this area is the possibility to use weather forecasts as input into disease models and consequently output true disease forecasts. As weather forecasts improve together with more accurate estimations of micro environmental variables useful for plant disease models, as such precipitation and leaf wetness duration, it will be possible to provide seasonal estimates of disease likelihood and forecast outbreaks. This is especially interesting for field crops for the reason that unnecessary sprays has a significant impact on production costs, and no timely applications may result in inadequate control.

The present work illustrates an approach towards that direction by the use of novel programming languages and technology for the development of a web-based prototype for model implementation and delivery. The case study is FHB, a disease of great concern for wheat production worldwide as well as for southern Brazilian wheat areas. Despite all research done for many years, the control of this disease is still challenging given its complex nature (McMullen et al. 1997) and some factors as dose rate, application timing and spray quality for adequate coverage of the spike tissues are key in fungicide efficacy for a good control (Reis 1986; Picinini and Fernandes 2001). FHB forecast models are considered an important tool for the decision-making, allowing producers to timely and effectively apply fungicides in conjunction with other control strategies (McMullen et al. 1997; Xu 2003). Different approaches for modeling this disease are found in the literature and comprehensive information on several FHB models has been reviewed (Del Ponte et al. 2004).

Critical knowledge on the epidemiology of a disease needs to be available in developing a decision support system. The epidemiology of FHB has been studied in southern Brazil since late 1980s. Climatic conditions are most suitable in that region, and disease has a periodical occurrence. The distinct climate conditions observed along the years have helped in identifying the main factors affecting regional epidemics. A mechanistic process-based simulation model, named GIBSIM, has been developed and

improved along the years with previous knowledge and a series of local studies on the interaction of pathogen, host dynamics, and the environment. The model has been validated with epidemic cases observed in Passo Fundo location, Brazil. The data has been collected on experimental plots in 5-years and distinct planting dates each year. The accumulated risk infection index simulated by the model explained 93% of variation in disease severity (Del Ponte et al. 2005). In this work, GIBSIM model is the core of a web-based prototype system designed to gather site-specific and forecast weather data and deliver true-forecasts for FHB for one location in southern Brazil.

25.2 Material and Methods

The web application, called GibSimWeb was developed based on the Model-View-Controller (MVC) design pattern. The model part is the business logic; the view presents images and data on WebPages; and the controller determines the overall flow of the application (Fig. 25.1). The server programs are: weather data management server (WDMS), database server (DBS), disease forecasting model server (DFMS), and web

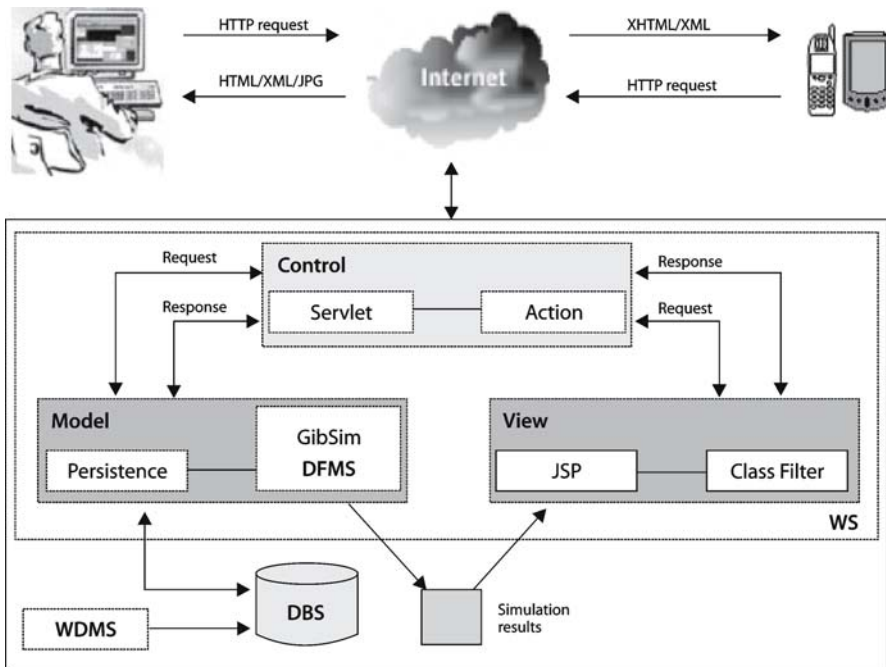


Fig. 25.1. Architecture of the web application designed for gathering and storing actual and forecast weather data to run a simulation model to forecast risk of Fusarium head blight of wheat. The server programs are: weather data management server (WDMS), database server (DBS), disease forecasting model server (DFMS), and web server (WS)

server (WS). WDMS consists of a module for weather data retrieval from automated weather stations located at remote sites. Data is updated at 10 minutes interval. In addition, forecast data, living on the INPE (National Institute for Space Research) databases is retrieved by FTP protocol. PostgreSQL is the core of DBS and stores weather data, as well the identifiers for weather station and run-time parameters such as cultivar, planting date, previous crop, etc. DBS is interfaced with WDMS and DFMS using a Java API, and with WS using an SQL module in a JSP script engine. WS retrieves information from DBS upon request by users through a client-side (web-browser) interface. In addition, it provides a simple request form for defining the run-time parameters. The output is displayed either in textual or graphical format by using a server-side plotting script. The system is also set to deliver simulation output to cell phones and PDA. Besides the option of defining a weather station in the database, the system allows users to input their own weather data, such as precipitation, temperature, relative humidity, etc. customizing the results for site-specific conditions.

The system uses either hourly or daily weather data from DBS, and DFMS produces daily risk infection index by using near real-time and anticipated risks by combining historical data with 7-day weather forecast. During the simulation, each sub-model uses data from WDMS. The daily output is a risk infection index calculated based on daily outputs from each sub-model. The forecast risk combines both historical and 7-days forecast of hourly weather data, generated by the ETA model using a grid of 40 km× 40 km. Since the model accounts for the effect of wheat development to estimate disease severity, the simulation starts on the day the first heads emerge in the field. At any time since then, actual as well as future weekly accumulated risk index is estimated. Once an accumulated risk level of concern is projected and the simulation is at the critical time for control, the model warns that fungicides may be needed.

25.3

Results and Discussion

The preliminary runs of GibSimWeb prototype showed that the system successfully collected hourly weather data including solar radiation, temperature, precipitation and relative humidity from Embrapa's automatic weather station and forecast data from INPE servers, and stored them in the DBS. After defining the location, heading date, and cultivar, the prototype is set to present the results in the webpage in a tabular (Fig. 25.2), graphical (Fig. 25.3) and report format (Fig. 25.4). The table shows model output and weather variables. The graph shows the daily increase of infection index, and some environmental variables. Infection indices and related risk are computed in a daily basis since first day of the simulation and the anticipated risk take into account actual and forecast data. The report is a summary and interpretation of the risk of outbreaks, that may be used to base decision-making. The reports are sent to emails and cell phone provided by registered users who set a specific date for heading and the system runs automatically on a daily basis using pre-set parameters. Numerical infection index is converted to 4 categorical levels (no, low, moderate and high epidemic risk) that will base decision-making on fungicide application, along with other factors. The GibSimWeb URL is <http://inf.upf.br:8080/gib/GibSimWeb.jsp>.

GibSim Simulator

Station:	EBPFWS <input type="button" value="v"/>		
Heading Date:	15/09/2005 <input type="button" value="4"/>		
Sowing Date:	<input type="button" value="4"/>	Cultivar:	BRS 179 <input type="button" value="v"/>

Simulation Results

Date	ST	Anthers	GZ	Inf	Gib	Total Gib.	Severity
15/09/2005	0	0	0,172	0	0	0	0
16/09/2005	0	0	0,302	0	0	0	0
17/09/2005	0	0	0,259	0	0	0	0
18/09/2005	0	307	0,249	0	0	0	0
19/09/2005	0,006	2090	0,205	0	0	0	0
20/09/2005	0,044	4378	0,159	0	0	0	0

Weather Forecast

Date	Tmin	Tmax	Tmean	RH	P	SRad	LWD
21/09/2005	15,8	22,4	19,1	91,5	3	2,6	0
22/09/2005	15,5	27,5	21,5	70,3	16,5	14,4	0
23/09/2005	16	23	19,5	96,3	10,5	1,3	0
24/09/2005	12,5	16	14,25	94	17,8	2,6	0
25/09/2005	14,4	24,4	19,4	82	21,1	14,1	0
26/09/2005	12,6	25,8	19,2	72,3	0	18,8	0
27/09/2005	17,2	28	22,6	83	0	11,3	0

Fig. 25.2. Computer screen showing model inputs and simulation results

The prototype proved functional and can be easily extended to other locations where automatic weather stations are available with the capability to send data to DBS using the same protocol. In addition, the system may contain modules to allow a user to set weather retrieval from his own on-site automatic station directly to the DBS or from there to his computer and access a local database, besides retrieving forecast data from INPE. Therefore, the user may run the model for his location from any computer or mobile device accessing the web. The user will have the option to either make his

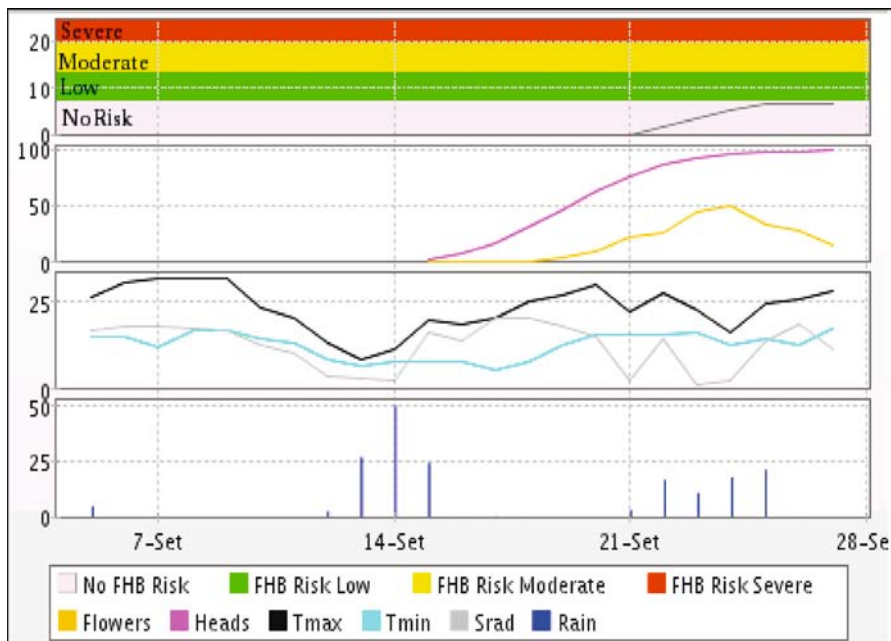


Fig. 25.3. Computer screen showing model output in graphical format

data public or private. This would be an alternative to computerized weather stations that are more costly.

A tactical utility of the web application for the management of FHB is the potential to improve disease control by allowing timely fungicide applications. When a high risk of outbreaks is anticipated, application of fungicides soon after infections, if weather permits, would help improve fungicide efficacy with a curative effect. Besides that, once weather data are available for several locations in a region, the model can be used to assess spatial variability of regional epidemic. Once long-term historical weather dataset is available for several locations in a production region, the model can be used to map climatic suitability for the epidemics. Effects of planting dates and crop rotations could be evaluated without the need of local experimentation. This system may also be used to hindcast past scenarios to test the accuracy of the system.

The modularity of the system allows the implementation of other disease models especially those requiring more complex data such as hourly weather information and leaf wetness duration. The disease simulator may be easily layered with crop models such as the CERES-Wheat from the Decision Support System for Agrotechnology Transfer (DSSAT) suite, using phenological data output by the latter (Ritchie et al. 1998). Fernandes et al. (2004), linked process-based models to assess the potential impact of climate change in the epidemics of Fusarium head blight in wheat growing regions in southern Brazil, Uruguay and Argentina.

FHB Risk Warning

Forecast starting in 09/21/2005

Model inputs:

Starting of Heading date: 09/15/2005

Cultivar: BRS179

Location: Passo Fundo

Simulation outputs:

Today is: 09/20/2004

Estimated peak of flowering: 09/24/2004

Accumulated infection risk today: 0.0

Accumulated 7-days forecast infection risk: 3.89

Projected severity: 6.43%

Interpretation:

Today is 4 days before peak of flowering date. Computer models are projecting a NO RISK of the disease reach epidemic levels in the next 7 days. No control measure is need at this time but scenario may change according to daily predictions.

Disclaimer:

The risk generated by computers models is under validation for areas other than Passo Fundo, RS, Brazil. Projected disease risk depends on weather forecasting for the next seven days, which has uncertainties. The information provided is experimental and offered to the public for informational purpose only and shall not be used for decision making of any kind. Embrapa Trigo, University of Passo Fundo and National Institute for Space Research - INPE or their employees assume no liability from the use of this information, nor do they warrant the fitness of the forecasts for any use.

Fig. 25.4. Fusarium head blight (FHB) simulation report

Acknowledgements

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Climate-Based Agricultural Risk Management Tools for Florida, Georgia and Alabama, USA

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26.1 Introduction

The Southeast Climate Consortium was initiated in 2001 as a regional expansion of the Florida Consortium. The Florida Consortium of Universities (FLC), consisting of the University of Miami, the University of Florida, and Florida State University was formed in 1996 and was funded by the U.S. National Oceanic and Atmospheric Administration-Office of Global Programs (NOAA-OGP) as a pilot Climate Applications Project. Following the establishment of the Regional Integrated Sciences and Assessment (RISA) program, the FLC became the first RISA east of the Mississippi. Initial research concentrated on the use of seasonal-to-interannual climate forecasts for the agricultural sector in Argentina. This focus was shifted to Florida in 1998. Following the success of the FLC in Florida, the University of Georgia was invited to join the consortium in 2001 and as a result the Southeast Climate Consortium (SECC) was formed. In 2002, Auburn University and the University of Alabama at Huntsville joined the SECC.

The SECC currently encompasses the three southeastern states of the USA, including Florida, Georgia, and Alabama. The climate of the region is complex and varied, and ranges from tropical in southern Florida to more temperate in the Florida panhandle, Alabama and Georgia. For instance, the annual average temperature in Georgia for 2004 ranged from 14 °C in the Georgia mountains to 20 °C in South Georgia. The El Niño-Southern Oscillation (ENSO) phases have a strong impact on the interannual climate variability in the region. El Niño typically results in a wetter winter and spring and a cooler winter, while La Niña typically brings a drier fall and winter, with a warmer winter for the entire region and a cooler summer, especially in northern Alabama and Georgia.

Agriculture and its associated agribusiness is the dominant economic sector. In Georgia alone the farm gate value for 2003 was more than U.S.\$9 859 million. Agriculture in the region is very diverse and includes poultry and eggs, livestock and aquaculture, and forages and row crops. The latter includes a wide range of crops such as the traditional row crops, e.g. maize, soybean, peanut, wheat, and cotton; vegetables and small fruits, e.g. strawberries, blueberries, and peaches; tropical fruit crops, e.g. citrus, as well as the emerging green industry with nurseries and turf grass. Long growing seasons allow for more than one crop to be grown during a year, especially for the shorter duration crops, such as fruits and vegetables. A crop rotation that includes multiple vegetables with staggered planting dates or wheat planted in the fall and harvested in June, followed by a late planted soybean are part of this varied cropping system.

Due to the variable weather and climate, irrigated cropping systems are very common, especially in Florida and Georgia. Close to 1.5 million acres were irrigated in Georgia alone in 2004. This allows farmers to mitigate potential droughts, such as the severe droughts that occurred in the late 1990s. As a result, the availability of water for agriculture has become an important issue due to the competition for the water needs among the public sector, especially the rapidly growing and expanding cities such as Atlanta, industry, agriculture and the need to maintain minimum water levels in streams and rivers for wildlife protection. Many of the rivers originate in Georgia and flow into eastern Alabama and the Florida panhandle. During the last two years of the drought, farmers located in the Flint River Basin in Georgia were paid not to irrigate their crops to guarantee minimum water flows into Florida. There is currently pending litigation between the states of Alabama, Florida and Georgia with respect to water allocation, sometimes referred to as the “water war.” Although stakeholders, including farmers, growers, producers and others in the agricultural sector, are somewhat familiar with weather-based information and tools, there is a definite need to provide more long-term information that is climate based and that can be used for strategic planning and decision-making, including long-term issues associated with drought and mitigation.

26.2 Methodology

The SECC combines expertise in atmospheric and oceanic sciences, agronomic sciences, systems analysis, decision support systems, and economic and social sciences. This provides a sound scientific basis to study climate and climate variability in the southeastern USA, to study the impact of climate and climate variability on agriculture and water resource management, to develop impact analysis and decision tools for stakeholders, and to assess stakeholder and clientele response and to obtain feedback for tool and information improvement.

Key to the approach of the SECC is to develop a close link between research and extension. This is facilitated by the land-grant system that includes the University of Florida, the University of Georgia, and Auburn University. In the USA these universities traditionally have had agricultural research and extension as their primary responsibility through the Agricultural Experiment Stations and Cooperative Extension Service (CES). In each state the CES has an extensive network of county coordinators and agents whose main role is to disseminate information to local farmers and growers. The county agents have established a close working relationship with these local farmers and developed their trust. The SECC is planning to train the county agents on climate and climate variability, the impact on agriculture, and the use of the web-based tools. The Office of the State Climatologist in each state also plays a key role in information dissemination, especially the preparation of climate outlooks and news releases.

Based on the initial feedback obtained from farmers, climate information is being developed at a local level, rather than at a regional level. The smallest scale at which currently information is being obtained is at the county level, with 67 counties each in Alabama and Florida and 159 in Georgia. Daily weather data have been obtained from the National Climatic Data Center (NCDC), which maintains the archives for the Cooperative Weather Observation Network, operated by the National Weather Service

(NWS). The weather records that are available include daily maximum and minimum temperature and precipitation. For most stations at least a 40- or 50-year record exists. Procedures have also been developed to generate solar radiation, based on the daily temperature and precipitation data. One weather station with the longest and most complete record is being assigned to each county. For counties where there is no local weather station, the closest weather station is being selected.

The decision support tools that are being developed are based on the crop simulation models of the Decision Support System for Agrotechnology Transfer (DSSAT). The main model is the Cropping System Model (CSM), which includes the grain legume model CROPGRO for soybean and peanut and the grain cereal model CERES for maize and wheat. A model for cotton is also being developed and experiments have been conducted for initial model evaluation. To establish model credibility, crop growth and development data have been collected in farmers' field for peanut, maize, and cotton. The state-wide variety trials are being used for determining the cultivar coefficients of the most common varieties.

26.3 Information Dissemination

A special website has been established for dissemination of climate information, crop management tools, and associated decision support systems. The website, www.AgClimate.org, allows for easy and rapid updating of information, such as climate outlooks and forecasts. One of the main tools is the climate tool. It includes a summary of the daily weather data base, described earlier. Once a user has selected his or her county, a monthly bar chart can be selected for each weather variable, e.g. maximum and minimum temperature, and rainfall. Based on the current ENSO phase or the ENSO phase selected by the user, different monthly means or totals are presented as well as deviations from normal. In addition, the monthly data for the previous five years can be displayed, as farmers normally have a clear memory of the past, especially with respect to extreme events. Options also exist to show cumulative probability functions and probability distribution functions for rainfall and temperature. An example is shown in Fig. 26.1 for Mitchell County, Georgia for average rainfall and deviation for El Niño; please note that the units are in English units.

The second tool is the yield risk tool, based on a summary of crop model simulations that have been run previously and have been stored in the database associated with AgClimate. The first crop for which extensive information has been developed is peanut, as it is one of main row crops in all three states and has been evaluated extensively with local data. In addition to the local weather data, the three dominant agricultural soil series have been identified for each county. The general and surface characteristics as well as horizon details are obtained from electronic databases of the United States Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS). The crop model is being run for all available weather years and three soil types for each county and a range of planting dates at weekly intervals that span the normal management practices of the region. The yield and yield components as simulated by the CSM model are stored in the AgClimate database. This provides quick and easy access to a summary of the simulated data for users, as it takes a significant amount of computer time to conduct these runs interactively. Similar to the climate tool, the

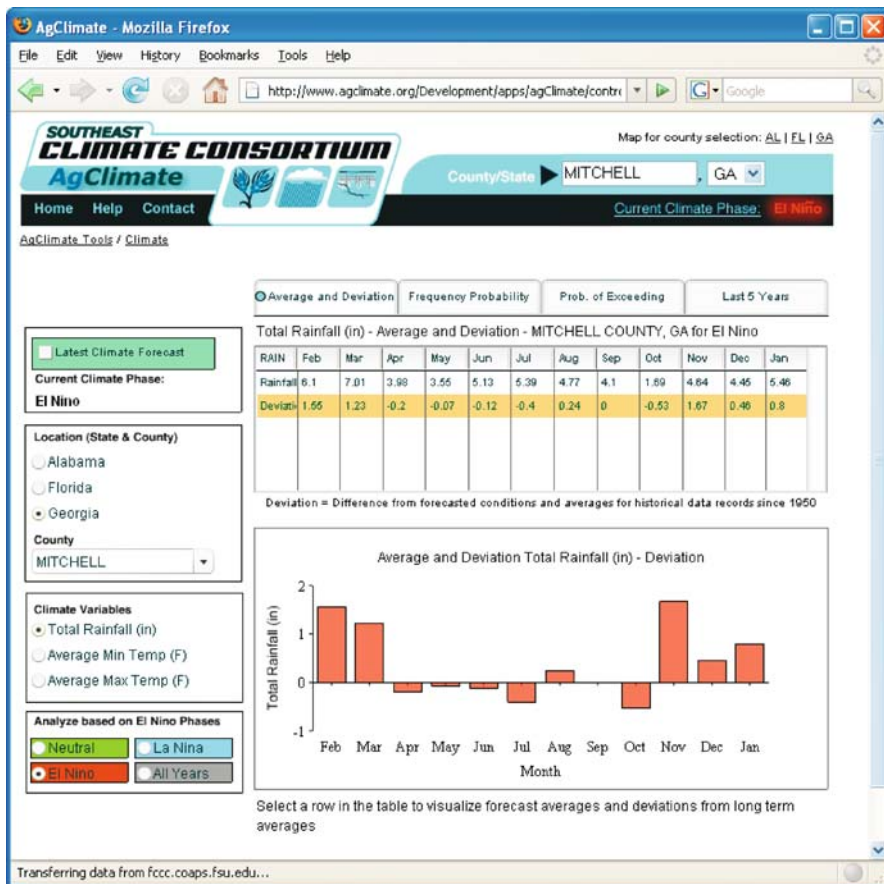


Fig. 26.1. Climate tool: average rainfall and deviation for the El Niño phase for Mitchell County, Georgia

user selects his or her county and one or more planting dates. The expected mean yield for each ENSO phase can then be displayed or the mean yield for the period of record. Due to the interannual weather variability the simulated yield is different for each year, Therefore, the yield can also be displayed as cumulative probability distribution functions or density histograms to account for the risks associated with each management selection or planting option. The yield tool is currently being populated for all peanut producing counties of the three states. An example for peanut for Mitchell County, Georgia, is shown in Fig. 26.2. Other crops that can be selected include tomato for south Florida and potato for the main potato producing county in Florida. Both crops were included based on prior activities of the FLC. Due to the wide range of crops, including those crops for which no computer models are available, some generic tools are also being developed, such as chilling hours and degree days with a range of base temperatures or threshold values.

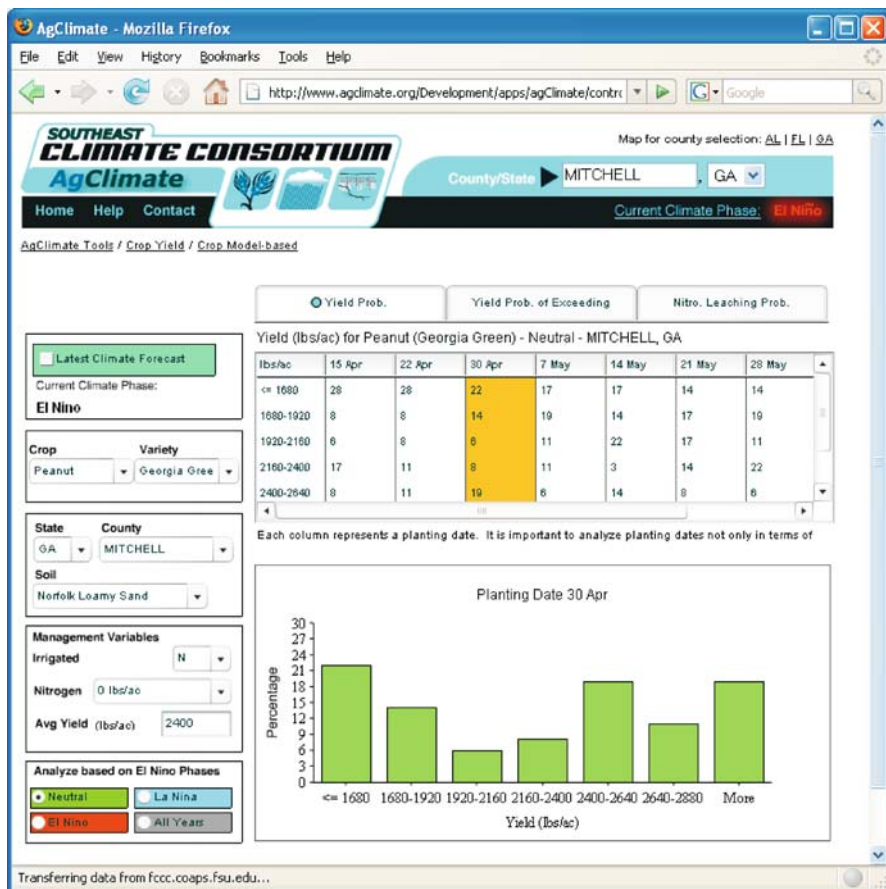


Fig. 26.2. Yield risk tool: average yield for peanut for the neutral phase for Mitchell County, Georgia

Initial introduction for the concept of the AgClimate was conducted in small-group meetings with county agents and extension specialists. Due to the positive response and feedback, a commercial company was contracted for a professional implementation of the research prototypes that were developed. The design of the website by this company has been rather generic and has allowed for easy modification and updating by personnel of the SECC, rather than having to rely on professional programmers. In addition, the design of AgClimate can also be easily migrated to other regions and/or counties as long as the underlying database is populated. Due to the fact that county agents are not very familiar with the concept of climate and its applicability in agriculture, several workshops have been held during the winter of 2005. AgClimate was also presented to two panels consisting of local farmers and extension personnel from Alabama and Georgia. Based on participation of the SECC team in the Georgia Peanut County Agent Training Workshops, we found that the county agents seem to need

an outlook of the expected local climate during the coming three to six months and a very clear prescription for associated management decisions with respect to which crop and cultivar to plant, when to plant and when to conduct pest, disease and weed management.

26.4 Evaluation and Impact Assessment

Weather and weather forecasts are part of the daily operation of farmers and producers. They can easily relate this information to the decisions they make, such as planting, irrigation management and pesticide applications. Although farmers are very much aware of extended droughts and the impact on their overall farming system, they do not always relate this to climate. The same applies to county and extension agents. The SECC, therefore, has implemented an evaluation and impact assessment team that will relay the needs and requests from stakeholders to the research team and develop a strong link between research and extension. It is expected that this team will also conduct user surveys and obtain feedback for impact assessment and evaluation of the usefulness of the climate-based tools and information. An initial survey was developed to evaluate how county agents perceive climate and its associated impact on crop production. This survey will be implemented on a state-by-state basis as our extension and outreach program develops. It was posted in December 2004, for the county agents in Florida and will be posted in May 2005 for the county agents in Georgia. This survey will be followed up with small-group meetings and personal interviews with county agents and producers.

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Key partners include the State Offices of Climatology for Alabama, Florida and Georgia to define research priorities and disseminate climate outlooks and forecasts and the Cooperative Extension Services for Alabama, Florida and Georgia and their extension network of extension specialists and county agents to disseminate climate-based information to growers, farmers and producers and to provide feedback for evaluation and impact assessment.

Climate Prediction and Agriculture: Lessons Learned and Future Challenges from an Agricultural Development Perspective

J. R. Anderson

27.1 Introduction

This opportunity to react to contemporary work on climate prediction in agriculture is a welcome one for someone who occasionally and mainly youthfully dabbled in the influence of climate in agriculture (e.g. Anderson 1970, 1979, 1981, 1985, 1991; Anderson and Dillon 1988a; Anderson and Hardaker 1973; Anderson and Hazell 1989), who was excited at the prospects for informative predictions (e.g. Byerlee and Anderson 1969, 1982; Anderson and Dillon 1992) but who has long since been far too remote from the action. Accordingly, to jump across the decades of progress, the point of departure taken here is the opening keynote address by Sivakumar (2006), in which the state of the art is succinctly summarized, albeit in a way that emphasizes the possibilities in a guardedly positive manner. Intriguingly, and seemingly properly in the view of this observer, he uses cautious words such as “could help” when charting the situations where climate forecasting efforts are intended to assist farmers and other agricultural managers in their decisions in the face of climatic uncertainty.

27.2 Need for the Assessment of the Value of Climate Forecasts

Workshop participants dealt variously with a variety of interrelated phenomena where sometimes use of terms was less cautious, particularly when skipping among “weather, climate, climate change, etc.”, where timescales are surely critical but open to opinion or interpretation. The paper of Meinke et al. (2006) was helpful in sorting out these semantics and thus spares such an attempt here, which had it been broached would have been heavily influenced by the recent work of Zillman et al. (2005). Suffice it to say that “forecast” and “prediction” cover many interpretations, such as: categoric vs. probabilistic; concrete/specific vs. descriptive; etc. so it is not too surprising that analysts and users are often talking at cross purposes. Indeed, such a use happens regularly in other related fields such as analysis of “risk”, “uncertainty”, “variability”, “vulnerability” – again, semantic issues for another time and place (e.g. Anderson et al. 1987; Hardaker et al. 2004).

The latter works just cited deal with measuring forecast value from what is usually referred to as a Bayesian perspective. In this view, information as encapsulated in some type of climate forecast has value when it can influence behavior/decisions. Such information usually also has a cost. So, whether it has positive net value is an empirical question that can be posed both before the forecast is issued, and after (*ex ante* and *ex post*). Evidence on this question has been sparse in this Workshop, although it would

seem that it should be a key item. One might be tempted to ask in the same vein, "Has CLIMAG been worth the investment in and around it?" The answer is not immediately obvious.

To return briefly to the Bayesian approach to forecasting in an uncertain world (in the spirit of Hardaker et al. 2004): prior probabilities attached to possible states of nature represent uncertainty held before a forecast; forecast information is captured in likelihood probabilities; posterior probabilities come from combining these and can serve as the updated weights to use in decision analysis. Such revision cycles can be treated sequentially, i.e. dynamically, in what constitutes an ongoing learning approach. But such an approach needs to be teamed up with models that represent production decisions about inputs and outputs, such as introduced by Msangi et al. (2006), as Eq. 27.1:

$$Q_t = f(X_t, Z_t, K_t, U_t) \quad (27.1)$$

where Q is typically multi-enterprise agricultural output, X is conventional inputs (e.g. land, labor, capital, conventional inputs such as fertilizer), Z is unconventional inputs (e.g. infrastructure), K is technical knowledge (e.g. R&D investment), and U is uncontrollable factors (e.g. weather). It is the fact of interaction between the X and the Z variables that gives probabilistic information on the Z s its potential value (e.g. Byerlee and Anderson 1969). Such production models are often estimated pragmatically, almost by definition simplistically and frequently badly but without some such, little can be done to bring climate forecast information explicitly into decision analysis and valuation of worth.

Estimation, whether done via econometrics, programming, or other methods (such as *ad hoc* simulation models built around crop growth models), is inherently demanding (e.g. Dillon and Anderson 1990): of conceptualization, including dynamics and participatory insights; of data, especially in LDCs; of estimational skills; of optimization skills; and last but not least, of interpretation skills. The work must also encompass modeling of behavioral factors, which adds to the challenge. For instance, representing risk and lifestyle preferences is a non-trivial step, although it seems reasonable to routinely allow for some degree of risk-aversion (Hardaker et al. (2004) argue for modest levels only). The ability of farmers to adjust should also usually be explicitly accounted, so part of the estimational challenge is to model the possible constraints to adjustment in response to emerging information. Farmers and others are all swimming in the stormy seas of risk, with or without formal climate forecasts. Are such forecasts a marginal part of the picture? This is a good question that can be answered only by careful empirical analysis. Needless to say, given the range of phenomena that must be modeled, a wide range of disciplinary skills is necessarily involved in such demanding research work.

Viewing climatic forecasting work as a particular type of research endeavor naturally raises the question of whether investment in it will be blessed with the same sort of typically high returns that have characterized more conventional agricultural research such as that related to crop improvement and productivity enhancement more generally (e.g. Alston et al. 2000). From the Sivakumar (2006) overview and the material presented at this workshop, it seems the evidence is not yet available to reach a solid conclusion on this, especially given the evident scarcity of formal accounting of the costs of climate prediction work. So, in the meantime, it seems analysts need to

strive to provide cogent evaluative evidence that can serve in part to deal with the implicit “competition” for funding that arises from mainstream agricultural research. Of course, some of the “conventional” research products that will have potentially high payoffs in responding to climate predictions present particular new evaluation tasks (e.g. appropriately valuing novel short-cycle cultivars that can “escape” or others that can better “endure” some droughts).

27.3

Climate Predictions and Risk Management

Research themes beyond the usual purview of conventional agricultural research are also necessarily involved in understanding the broad context in which climate prediction research takes place. At the risk of stating the obvious, there is clearly a need to better understand the mechanisms that diverse rural communities use for: managing risk, e.g. borrowing finance, selling assets, choosing technologies, etc.; coping with risk, e.g. calling on friends and relatives in times of need; shifting from risk, e.g. migrating, on a temporary or permanent basis, and so on – a field too large to delve into here (but see e.g. Anderson and Roumasset 1996; Anderson 2003). Agro-meteorologists may not have spent much time grappling with rural financial systems, futures markets, etc. but maybe they will have to do so increasingly? Or perhaps they may elect to work in more engaged manners with research workers who do focus on such themes?

Finally, to return to the title of this brief perspective, some policy dimensions pertaining to climate prediction work should be noted, inevitably reflecting efforts past (e.g. Anderson et al. 1987; Anderson and Dillon 1988b) and more recent (e.g. Anderson and Hazell 1997; Anderson 2000, 2003). As climate predictions inherently serve to modify the environment in which farmer choice is made, good policy making should logically be founded on good understanding of farmer risk management more generally, since climate is just one of the risks in that environment. In some countries uncertainty about property rights (especially land) may be of profoundly greater significance than climate outcomes, especially which it comes to on-farm or within-supply-chain investment decisions. Other enabling aspects such as private sector development (PSD) naturally impinge on decisions more generally, in what are increasingly alluded to as investment climate limitations. The world has largely entered an era where novel financial instruments (such as warehouse receipts, forward contracts, etc. largely provided or managed by private suppliers) can be used for more effective risk management, whether risks arise from the natural environment such as climate or from the economic and political environment (e.g. Larson et al. 2004).

One aspect of PSD of direct consequence for climate prediction is the state of development of the insurance industry in areas that are targeted by climate predictors. There are many contemporary developments in this industry that expand the opportunities open to risk managers along the whole chain from plot to plate. In particular, new products based on *index* insurance are becoming increasingly available, such as rainfall insurance (e.g. Hess 2004; Hess and Syroka 2005). Given the dependence of such instruments on the timely availability of reliable meteorological data, this provides a natural point of intersection between the climate forecasting community and the agricultural risk management community.

27.4 Climate Policy and Climate Predictions

Other communities are also relevant as climate forecasters reach out to their diverse clients. Those who plan emergency policy and intervention are members of one such group, and it seems that implementation of improved safety nets is something of a growth industry around the developing world, and is one that needs to be informed by the fruits of research on climate forecasting. Climate policy making is still usually something of an infant industry but is surely one that should be closely linked with climate research. So, the agenda for climate predictors is large, diverse and challenging (including the closer attention to monitoring and evaluation that Sivakumar called for at the outset of this workshop), and would-be predictors are to be enthusiastically assigned every good wish for success as they emerge from a honeymoon phase for what should ultimately be socially valuable contributions to the future of agriculture and humanity on which it depends.

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Conclusions and Recommendations

M. V. K. Sivakumar · J. Hansen

28.1

Conclusions

Participants in the workshop concluded that:

1. Over the past decade there were some developments that enhanced our knowledge of climate prediction applications in agriculture. These include the following:
 - There has been increasing collaboration between climate and agricultural scientists towards effective use of climate forecasts.
 - There has been quite a significant improvement in climate prediction models at the global level, especially with regard to prediction skill, understanding of processes, assimilation of data and methods to process output. Atlantic and Indian ocean components of the models have become more important.
 - Agricultural research has advanced knowledge and methodology, including simulation modeling, required to use climate information effectively.
2. Currently, end users of climate predictions encounter difficulties in understanding the terminology and formats that climate institutions use to delivering forecast and other information, especially the nature of uncertainty. Users are not familiar with the distinction between weather and climate forecasts.
3. Intermediaries (e.g. agricultural extension agents) have limited understanding in using climate forecasts for applications in agricultural decision-making.
4. There are limited curriculum resources and training opportunities on the application of weather and climate (forecast) information at all levels, including applied researchers, extension intermediaries, policy makers, and for training trainers at the university level.
5. Local institutional (e.g. capacity of extension services to use agriculture simulation tools) capacity to support climate applications at the farm level is variable but generally inadequate.

28.2

Recommendations

28.2.1

Science

General

1. Promote collaboration among scientists from the relevant climate and agricultural disciplines.

2. In applications, take advantages of potential cross-sector synergies between climate, agriculture and food security, water and human health.
3. Improve the capacity of agricultural and climate scientists to understand and exploit relevant information available on the World Wide Web. Promote workshops to train people on how to mine and interpret such data.
4. Enhance the ability of the community to integrate the output of Global Circulation Models (GCMs) with environmental monitoring based on remote sensing.
5. Stimulate research on linkages between models:
 - How crop models can incorporate GCM outputs and remote sensing information.
 - How GCMs can incorporate crop model outputs.
6. Promote greater involvement with *all relevant stakeholders* to better understand the decision problems and processes, and develop decision tools.
7. Identify “hotspots” for climate applications based on a global assessment of vulnerable regions where forecasts skills are high and capacity exists to use climate information to manage risk.
8. Expand economic analyses of the benefits of climate prediction applications.

Climate

9. Include soil moisture (through satellite observations) to improve the predictions of climate forecast models.
10. Develop common measures of forecast skill and quality to allow robust comparisons among different forecast systems.
11. Conduct research to develop user-oriented verification systems of the forecasts (include statistical, mathematical, and economic sciences to address this issue).
12. Since GCM outputs contain more information than is currently being released, assess the potential use of GCM outputs to predict the onset of rainfall season for regions where this subject is an important issue. Climate centers should include experienced evaluators who are familiar with the characteristics of the region targeted to help interpret and evaluate GCM outputs beyond the seasonal climatic means that are routinely released.
13. Address the issues of downscaling, GCM uncertainty and available observations, especially in developing countries.
14. Enhance capacity building on operational meteorology in different regions of the world.
15. Expand the scope of the seasonal climate prediction and incorporate the whole spectrum of climate variability (from intra-seasonal to climate change issues).
16. Promote linkages between climate modelers and local meteorologists to develop sound empirical forecast models.

Agriculture

17. Develop specific modeling tools for analyses at different spatial scales.
18. Improve the current crop simulation models and incorporate more physiologically based processes in order to make them more robust.
19. Develop procedures for updating crop model parameters on a regular basis (especially genetic coefficients).

20. Promote establishment of regional networks for standardized crop observations.
21. Move economic analyses beyond a focus on single crops toward modeling cropping systems, integrated crop-livestock systems and whole farm modeling.
22. Through the International Consortium for Agricultural Systems Applications (ICASA), promote a globally-coordinated initiative in crop modeling and systems analyses for model improvement, model comparison and capacity building.

28.2.2

Capacity Building, Network Development and Institutional Partnership

Increasing farmers prosperity through better use of climate science and associated applications must consider the following aspects:

- Capacity building for climate producers, intermediaries and users (farmers).
- Development of networking among stakeholders.
- Strengthening the institutional partnerships.

Capacity Building

23. Given that the science of climate forecasting and applications is relatively recent, it is important to undertake capacity building activities at all levels from climate forecasting to national agricultural research systems to intermediaries to the farm level, especially in developing countries.
24. The focus of capacity building activities for different levels of stakeholders should be formulated according to their needs through an end-to-end capacity building approach involving all stakeholders in the process in order to ensure effective feed back from users to climate producers. Hence training should be organized for:
 - Producers of climate information – to produce climate information products in a form that is simple and easy to understand.
 - Agriculture scientists in research agencies and universities – to support climate forecast applications and develop recommendations for effective farm-level adaptation strategies to climate risk.
 - Communication agencies (e.g. media) – in broadcasting climate forecast information in such a way as to assist the user communities in formulating appropriate actions.
 - Extension workers and community-based organizations – to deliver climate forecast application technologies to end-users (e.g. farmers) and assist them in using the technologies.
25. Given that climate application is generally not included in the curricula of agricultural universities, the Agricultural Meteorology Division and the Education and Training Department of WMO should review this issue and work with agricultural universities to include climate forecast modules in their academic curriculum.
26. There is a need to train national agencies in climate prediction applications in agriculture, so they can share the knowledge with extension agents or other intermediaries, and with for policy makers to increase their awareness of climate applications in agriculture.

Networking and Institutional Partnership

27. Strengthen networking and institutional partnership through:
 - Linking all relevant national organizations to form strong partnerships with each other and with the global programs initiated by United Nations Agencies, such as WMO and FAO; and International Organizations such as CGIAR, IRI, START; and Regional Organizations such as ACMAD and AGRHYMET.
 - Establishing a web-based network among national, regional and international organizations and agencies that can facilitate development of end-to-end systems for applying climate forecasts in the agriculture sector and, policies to address current and future climate risks.
 - Linking individuals who work actively in the area of climate forecast application in agriculture through an informal web-based network and other means that will help them further develop their capacity to support climate applications in agriculture in the broadest sense (including technical, socio-economic and institutional aspects), and access information on advancing of climate application technologies, funding sources, data, tools, and periodical meeting/conferences on climate applications.
 - Including representatives from the scientific community who work in the concerned area on a Steering Committee for the proposed networks.
28. Document success stories, failures and lessons through case studies to demonstrate the real value of climate information to agricultural communities and scale up from case studies to regional and global scales.

Climate Outlook Forums (COFs)

29. Adopt a holistic approach to COFs including different sectors such as agriculture, hydrology, health as well as media.
30. Explore alternative ways of conducting regional COFs with more active participation of stakeholders.
31. Improve COF systems (terms, applications) by establishing a consortium (farmers, researchers, etc.), to seek funds to conduct future regional COFs.

28.2.3

Other Recommendations

32. Develop a common language for the dialogue between climate information producers and end-users.
33. Streamline communication systems for delivery of climate information to end-users.

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