Integrating seasonal climate prediction and agricultural models for insights into agricultural practice

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Interest in integrating crop simulation models with dynamic seasonal climate forecast models is expanding in response to a perceived opportunity to add value to seasonal climate forecasts for agriculture. Integrated modelling may help to address some obstacles to effective agricultural use of climate information. First, modelling can address the mismatch between farmers' needs and available operational forecasts. Probabilistic crop yield forecasts are directly relevant to farmers' livelihood decisions and, at a different scale, to early warning and market applications. Second, credible *ex ante* evidence of livelihood benefits, using integrated climate–crop–economic modelling in a value-of-information framework, may assist in the challenge of obtaining institutional, financial and political support; and inform targeting for greatest benefit. Third, integrated modelling can reduce the risk and learning time associated with adaptation and adoption, and related uncertainty on the part of advisors and advocates. It can provide insights to advisors, and enhance site-specific interpretation of recommendations when driven by spatial data. Model-based 'discussion support systems' contribute to learning and farmer–researcher dialogue. Integrated climate–crop modelling may play a genuine, but limited role in efforts to support climate risk management in agriculture, but only if they are used appropriately, with understanding of their capabilities and limitations, and with cautious evaluation of model predictions and of the insights that arises from model-based decision analysis.

Keywords: seasonal climate prediction; crop model; impact assessment; yield forecasting

1. INTRODUCTION

There is a strong history of integrated climate–crop models to estimate the impacts of climate change scenarios, and adaptive breeding and land use strategies. Advances in climate prediction at a seasonal lead-time have stimulated substantial interest in forecasting crop yields as a means of improving farm management and policy-level interventions in a manner that reduces risk and enhances livelihoods and food security, particularly in the marginal, rainfed, tropical cropping regions that the green revolution largely bypassed.

Farmers experience climate change not as a shifting mean but as climatic variations. Climatic variability at all of its time-scales is, therefore, a current challenge to development. Furthermore, developing flexible, proactive strategies for managing year-to-year climate variations within farming communities and the institutions that interface with them, using advance climate information, is arguably the most concrete step that the agricultural enterprise can take to build resilience to long-term changes in the global climate system. These two realizations appear to be bringing the historically distinct global change adaptation and agricultural development agendas closer together, particularly in Africa.

Several research groups are seeking to advance methodology to integrate crop simulation models with dynamic climate forecast models for application at a range of spatial scales. A range of promising approaches has emerged (Hansen *et al.* submitted*b*) that may have relevance to management of climate variability and application to climate change projections. In this paper, I seek to put such work in context by discussing how integrated climate–crop models operating at a seasonal lead-time might contribute to efforts to address climate-related constraints to agricultural development, with some emphasis on rainfed agriculture in Africa. Section 2 summarizes the role of climatic risk and potential role of seasonal climate prediction in agriculture. Section 3 relates integrated climate–crop modelling to constraints that have been identified to effective use of seasonal forecasts within agriculture. The three subsequent sections propose three areas in which integrated modelling might contribute to more effective use of seasonal climate forecasts for the benefit of smallholder agriculture in the developing countries.

2. CLIMATE RISK AND AGRICULTURAL DEVELOPMENT

Climate exerts a profound influence on the lives of poor rural populations who depend on agriculture for

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livelihood and sustenance, who are unprotected against climate-related diseases, who lack secure access to water and food, and who are vulnerable to hydro-meteorological hazard. The year-to-year variability of rainfall is a significant constraint to the sustainability of rainfed farming systems in poorer countries of the tropics. This argument is developed more fully in Hansen *et al.* submitted*a*. Climatic extremes, such as drought and flooding, have a direct and often persistent impact on farmers' assets and livelihoods (Dercon 2004). Perhaps, more important (Elbers *et al.* 2003), the uncertainty associated with climate variability creates a moving target for management, and is a disincentive to sustainable resource management, and to the intensification and adoption of innovation that is necessary for secure livelihoods and long-term rural prosperity.

> …Variability by itself is not necessarily welfare-decreasing if it is anticipated and acted upon. Surprise, however, has adverse consequences since the optimal *ex post* and *ex ante* choices rarely coincide
>
> (Hallstrom 2004)

Rainfall variability tends to be the dominant source of livelihood risk in smallholder rainfed agriculture, particularly in dryer environments (Walker 1991; Rosenzweig & Binswanger 1993; Dercon 2002; Zimmerman & Carter 2003). In the face of climatic uncertainty, risk-averse farmers employ conservative strategies, including avoidance of improved technology, under-use of fertilizers and shifting from productive to non-productive liquid assets. In sub-Sahara Africa, where soil nutrient depletion is now recognized as a root cause of declining per capita food production and a critical constraint to sustainable livelihoods (Stoorvogel & Smaling 1990; Sanchez *et al.* 1997; Sanchez 2002), the apparent effect of climatic uncertainty on investment in soils (Bliss & Stern 1982; Binswanger & Sillers 1983) is a particular concern. These *ex ante* strategies, designed to buffer against climatic extremes, substantially reduce average income and marginal productivity of assets, and do so disproportionately for the relatively poor (Rosenzweig & Binswanger 1993; Zimmerman & Carter 2003).

Despite the tremendous concern about climate change, climate variability has not received as much attention as other development issues, in part because it has been considered part of the environmental baseline that is not amenable to intervention. Climate variations in the months ahead no longer need to be accepted as a total unknown. The chaotic nature of the atmosphere restricts deterministic prediction of weather events to lead-times of several days. However, year-to-year variations in the atmosphere are influenced by interactions between the atmosphere and the more slowly varying ocean and land surfaces, such as those associated with the El Niño-Southern Oscillation (ENSO) in the tropical Pacific. Improvements in our understanding of interactions between the atmosphere and its underlying surfaces, advances in modelling the global climate system, and substantial investment in monitoring the tropical oceans now provide a degree of predictability of climate fluctuations at a seasonal (i.e. several months) lead-time in many parts of the world.

Goddard *et al.* (2001) provide a useful, recent review of the scientific basis and methodology of seasonal climate prediction. Where the necessary conditions are in place or can be put into place, seasonal climate prediction offers an under-exploited opportunity to manage climate variability: to respond proactively to adverse conditions and exploit favourable conditions.

3. INTEGRATED CLIMATE–CROP MODELLING AND THE CLIMATE RISK PROBLEM

The potential for seasonal forecasts to reduce the adverse impacts of climate variability and enhance rural livelihoods has motivated a number of pilot studies targeting smallholder farmers in developing countries. Several pilot studies with African farmers have demonstrated a high level of interest and have identified a range of promising livelihood management responses (Ngugi 2002; Tarhule & Lamb 2003; Ziervogel 2004). They have also identified several obstacles to using seasonal forecasts effectively to reduce the adverse impacts of climate variability and enhance rural livelihoods. I highlight three for which integrated climate–crop modelling has a potential role. The first is a mismatch between farmers' needs and the scale, relevance and transparency of available forecasts (O'Brien *et al.* 2000; Ingram *et al.* 2002; Patt & Gwata 2002; Ziervogel 2004). The second is the cost, risk and learning time farmers face during adaptation and adoption (Patt & Gwata 2002; Ziervogel 2004). Third, I propose that failure to obtain adequate institutional, financial and political support is also a key constraint. Farm-scale studies have identified several resource constraints (Vogel 2000; Phillips *et al.* 2001; Ingram *et al.* 2002; Phillips 2003) that limit responses to advance climate information, but that might be amenable to intervention if additional institutional actors (e.g. suppliers of production inputs and credit) are engaged. Scaling up beyond plot studies will require substantial investment on the part of national agricultural and meteorological services. Providing comprehensive institutional support, including provision of relevant climate information, appropriate technical guidance and intervention in financial services and production inputs (Hansen *et al.* submitted*a*) will require the involvement of a broader range of institutions that have typically been involved in pilot studies.

Several research groups who are working on applications of seasonal climate forecasts have invested heavily in the use of crop simulation models. Although, the use of weather data from analogue years associated with, e.g. ENSO phases, has been the standard approach, interest in coupling crop simulation with dynamic climate forecast models has increased substantially in recent years. A mismatch between the scale of dynamic climate models and crop simulation models complicates the task (Hansen & Indeje 2004). Crop growth depends more on the distribution of weather within a season than on the season averages that forecasters typically provide. Crop simulation models, generally, assume the small-scale of a homogenous plot, and simulate dynamic interactions between weather, management and crop growth and

development on a daily time-step. On the other hand, the spatial resolution of the current generation of general circulation models (GCMs) is on the order of 10 000 km^2. Although, GCMs simulate the atmosphere on a sub-daily time-step, the spatial averaging within grid cells distorts day-to-day variability, with potentially serious consequences for simulated crop responses (Baron *et al.* 2005). Fortunately, recent and ongoing research has given rise to several promising approaches to translating seasonal climate forecasts into probabilistic predictions of crop response (reviewed in Hansen *et al.* submitted*b*).

It is clear that applications of seasonal climate forecasts to manage risk are concerned with impacts on, e.g. crops and not climate *per se*. Yet, the most critical opportunities and challenges have more to do with institutional support than technology. If that is the case, then what contribution can agricultural models integrated with seasonal climate prediction models make? I propose three promising contributions: (i) translating seasonal climate forecasts into useful information; (ii) *ex ante* assessment of potential benefits and (iii) fostering and guiding application.

4. TRANSLATING CLIMATE FORECASTS INTO USEFUL INFORMATION

Hammer (2000) argued that seasonal climate forecasts have no intrinsic value. First, value comes from improved decisions not information. Second, it is not climatic means but impacts within the system being managed that are relevant to decisions. If climate forecasts are to have value, they must modify decision makers' expectations of the production or economic outcomes that relate to goals, within the system being managed (Luseno *et al.* 2003). Crop models integrated with seasonal climate forecasts provide a means of translating forecasts of seasonal climate anomalies into forecasts of production impacts. The nature of the decision determines the appropriate spatial scale and lead-time of crop forecast information.

(a) *Farm level applications*

Producers of annual crops must routinely make a range of critical production and livelihood decisions prior to planting that interact with climate, but whose outcome is not realized until harvest several months later. Where predictability is sufficient, seasonal forecasts may provide probabilistic information about crop yields with sufficient lead-time to influence pre-planting decisions. A mismatch between the content, scale, format and lead-time of available operational climate forecasts, and the information that farmers need for such decisions, is the most often cited constraint to effective use. It is also the constraint that is most within the control of climate information providers.

Although, farmers' information requirements are somewhat context-specific, a few generalizations emerge from experience in a range of contexts. Farmers need information that: (i) can be interpreted at a field scale (O'Brien *et al.* 2000; Jochec *et al.* 2001; Letson *et al.* 2001; Ingram *et al.* 2002); (ii) includes information about timing beyond three-month climatic means (Nelson & Finan 2000; O'Brien *et al.* 2000;

Phillips & McIntyre 2000; Ingram *et al.* 2002); (iii) is explicit about accuracy (Childs *et al.* 1991; O'Brien *et al.* 2000; Ziervogel 2004); and (iv) is expressed in terms of impacts and management implications within the agricultural systems that they manage. In contrast, operational climate forecasts are typically expressed as three month climatic means averaged over large areas. When accuracy is communicated, it is typically expressed as shifts in the probability of experiencing outcomes within each climatological tercile, with no information about how the probabilities are derived.

The widespread awareness associated with the 1997 El Niño event stimulated a great deal of interest and debate about the potential value of climate prediction to poor farmers in developing countries. Some expressed doubts about the feasibility of meeting farmers' information requirements. Is predictability of climate and crop response at the farm scale sufficient to be useful? If not, will responding to forecasts that could be wrong expose farmers to unacceptable risk? Barrett (1998) expressed concern that the level of predictability of crop yields at a farm scale is likely to be inadequate for use by risk-averse smallholder farmers. First, fine-scale spatial variability of rainfall implies that seasonal rainfall predictability is limited to aggregate spatial scales. Second, because crop yield is not a simple function of seasonal total rainfall, the accumulation of errors going from seasonal climatic predictors (e.g. sea surface temperatures), to local seasonal means, to crop response implies that predictions of impacts such as crop response will be less accurate than predictions of climatic means. Barrett called for greater investment in methods for translating climate forecasts into forecasts of relevant farm-level impacts.

Averaging in either time or space tends to increase prediction skill by reducing the random 'noise' component of variability in weather. As Gong *et al.* (2003) demonstrate, the skill of GCM-based seasonal climate forecasts tends to increase with increasing spatial aggregation relative to a single GCM grid cell in several parts of the world. For the state of Ceará, in northeast Brazil, they also showed that downscaling to individual single stations reduces prediction skill, but that a substantial proportion of the predictability remains (figure 1). Although limited experience seems to support the generalization that forecasts that are skilful at an aggregate scale show only moderate decline at individual points, there remains a need to evaluate the influence of scale of aggregation on prediction skill systematically in a range of locations.

The argument that predictability of agricultural impacts is necessarily less than that of climatic means overlooks two considerations. First, information (e.g. antecedent rainfall, stored soil moisture) beyond seasonal climatic anomalies can contribute to predictability of crop response. Second, predicting relevant impacts directly from climatic predictors instead of from predicted climatic means reduces accumulation of errors, and potentially incorporates information about rainfall distribution and other relevant meteorological variables that are embedded in climatic predictors, but lost when converting them into seasonal rainfall totals (Rosenzweig 1994).
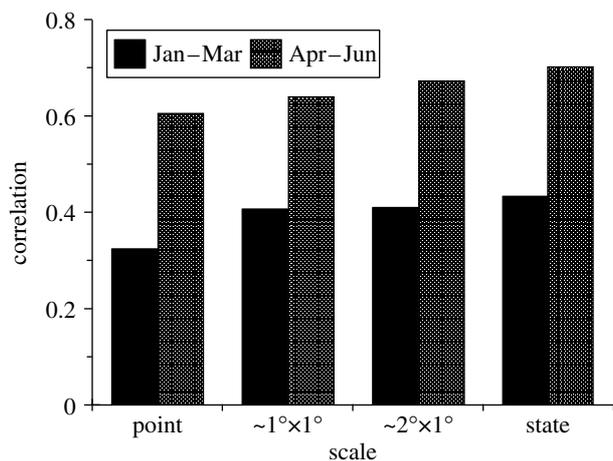
Figure 1. Correlation of observed versus predicted rainfall in the state of Ceará, northeast Brazil, as a function of scale of aggregation. Source: Gong et al. 2003.

In a paper that arguably stimulated much of the interest in using seasonal forecasts to benefit farmers in Africa, Cane *et al.* (1994) showed that ENSO-related sea surface temperatures in the Pacific were correlated more strongly with maize yields (1970–1993) than with rainfall averaged across Zimbabwe. Dilley (1997) found that maize yields in Oaxaca, Mexico, were correlated more strongly with the Southern Oscillation Index than with local rainfall. K. P. C. Rao (ICRISAT, Nairobi 2004) and I used the APSRU model to simulate maize yields for the short rains season at Katumani, Kenya, as a function of observed weather and GCM-based monthly hindcasts disaggregated to daily values using a stochastic weather generator. Correlations between predictions and observations were higher for simulated yields than for seasonal rainfall totals (figure 2), although the analysis did not account for crop model error. By integrating GCM-based seasonal rainfall forecasts into an operational regional wheat forecasting system in Queensland, Australia, Hansen *et al.* (2004) showed that reported district yields were more predictable than seasonal rainfall totals. They attributed this in part to the influence of observed antecedent rainfall and resulting soil moisture storage on subsequent yields. I anticipate that methodological advances and empirical evidence will address concerns about the predictability of crop response to climate fluctuations. Yet, given the spatial heterogeneity, multiplicity of yield-reducing factors and paucity of data in rainfed farming systems of much of Africa, realistic, site-specific forecasts of crop yields are likely to be elusive for some time.

(b) Early warning, market and policy applications

Advance information about crop production is relevant to decision-makers operating at a range of scales from field to national or regional, whose decisions impact the welfare of farmers. Institutions responsible for responding to drought or food crises and traders and investors in commodity markets, are interested in anticipating production at relatively large spatial scales. Because of the adverse impacts of variability on commodity prices, the use of advance information about production to
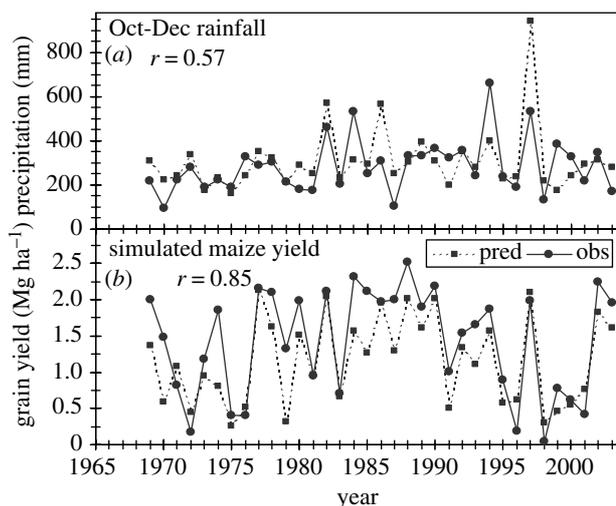

Figure 2. (a) Predicted and observed October–December rainfall and (b) simulated maize yields, Katumani, Kenya. Maize yields are from APSIM run with 20 realizations of stochastic rainfall disaggregated from monthly hindcasts, 40 kg ha^{-1} applied N fertilizer, stand density of 3.5 m^{-2} (courtesy of K. P. C. Rao, ICRISAT Nairobi). Maize yields simulated with observed rainfall serve as the benchmark for comparison. Rainfall hindcasts are based on a linear transformation of ECHAM four simulations, forced with observed SST boundary conditions (Hansen & Indeje 2004).

manage markets for staple foods to stabilize prices is appealing from the standpoint of food security. Although, experience with using climate information to intervene in markets is still limited, economy-wide modelling in Mozambique suggests considerable potential aggregate benefits of market applications of climate forecasts (Arndt & Bacou 2000; Arndt *et al.* 2003).

In food-insecure regions of Africa, early warning systems based on remote sensing of rainfall and vegetation, and monitoring of local commodity markets, provide early indication of likely food shortfalls (Verdin & Klaver 2002). When a crisis requires external food aid, it can take several months to verify shortfalls, mobilize donors, transport food to the region and distribute it to the affected population. As a result, assistance often reaches the affected people after they have already suffered adverse health effects, divested productive resources or migrated away from their farms (Broad & Agrawala 2000; Haile 2005). Food aid organizations in Africa are increasingly interested in seasonal climate forecasts because of their potential to increase lead-time. For example, in August 2004, stakeholders concerned with food security early warning and response in East Africa initiated a periodic food security outlook forum, associated with the Greater Horn of Africa Climate Outlook Forum, with the goal of projecting likely food security impacts associated with the climate outlook to inform response (Ericksen 2004).

In contrast to many climate-sensitive decisions at the farm level, market and food security early warning applications can often use forecast information at various points within the growing season. The combination of increased spatial scale (Gong *et al.* 2003) and usefulness of forecasts at shorter lead-times increases the predictability potentially available for such

applications. On the other hand, institutional constraints to responding to food crises (Broad & Agrawala 2000) are likely to require a higher threshold of forecast certainty than individual livelihood decisions.

Operational crop forecasting systems exist in many regions to support market and policy applications (e.g. Motha & Heddinghaus 1986; Cantelaube & Terres 2005) and food security early warning systems (e.g. Verdin & Klaver 2002). These are often based on monitoring weather and crop conditions during the growing season. In some instances, they incorporate regionally calibrated crop models to simulate growth or water stress up to the current point within the growing season, then sample weather for the remainder of the season from past years to estimate yield forecast uncertainty. Skilful seasonal forecasts provide additional information that can increase the accuracy of within-season production forecasts based on monitoring and simulation alone, particularly early in the growing season (Stephens *et al.* 2000; Hansen *et al.* 2004; Cantelaube & Terres 2005). Integrating probabilistic forecasts of food production from integrated climate–crop models into models of household vulnerability (Dilley & Boudreau 2001) has potential to improve aid assessments and targeting at a relatively long lead-time.

5. *EX ANTE* ASSESSMENT OF 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. Because the use of seasonal climate forecasts within agriculture is a relatively new innovation, *ex ante* methods are, in most cases, the only way to estimate their benefits. Pilot studies have compiled some evidence of use of forecasts for farm decisions, but have, generally, not tried to quantify the resulting production or livelihood benefits. Even after farmers learn to use forecast information routinely, *ex post* assessment of benefits would require multiple years due to the stochastic nature of climate variability and forecast responses—longer than typical funding cycles allow. Furthermore, there are few, if any, regions in the developing world where rural communities have had access to operational climate information tailored to their needs for sufficient time to allow *ex post* assessment of use and benefits.

Ex ante impact assessment serves two related roles in applied agricultural research: providing evidence of potential benefit of proposed interventions to support mobilization of resources, and providing insight to target interventions where the positive impact is likely to be greatest (Thornton submitted). Resource mobilization has to do with allocation of scarce resources between a particular intervention or institution, and others that compete. Targeting relates to an institution or program's allocation of scarce resources among its own competing activities.

(a) *Confidence and credibility*
Increasing competition for dwindling resources for applied research has driven the international agricultural research community to become proactive about

both quantifying the benefits of past activities (i.e. *ex post* impact assessment), and providing evidence of the likely benefits of proposed interventions (i.e. *ex ante* assessment). Likewise, donors increasingly require *ex ante* evidence of benefit before they will invest heavily in new agricultural innovations. The application of seasonal climate prediction is a new innovation that potentially competes for scarce resources with technologies such as crop genetic improvements that have relatively long records of *ex post* evidence of impact. On the positive side, it shares with integrated natural resource management (INRM) a relatively short history, heavy demands on management and context-specific implementation that prevent robust *ex post* impact evaluation (Barrett 2003). Yet, the broad suite of interventions that fall under INRM are generally well funded within the international agricultural research community. Climate applications face the additional challenge of engaging climate and agricultural institutions that often do not have a history of substantive cooperation.

Although, there are good theoretical reasons to expect that farmers and other agricultural stakeholders should benefit (§2), there are still few well documented *ex post* demonstrations of adoption and benefit in developing countries, relative to many other agricultural development interventions. Some rather fundamental expressions of doubt about the potential utility to farmers in developing countries appear in the literature, citing examples of lack of use and barriers to use of available seasonal forecasts by smallholder farmers (Hulme *et al.* 1992; Blench 1999; Broad & Agrawala 2000; Eakin 2000). Hansen (2004) summarizes some of these concerns in a set of questions: is there enough predictability at the farm scale to be useful? Do smallholder farmers have the capacity to respond to climate forecasts? Will climate forecasts that could be wrong expose farmers to unacceptable risk? Can smallholder farmers with limited education understand probabilistic climate forecasts? Is the application of seasonal climate forecasts inherently biased against the poor? With the exception of farmers' ability to understand probabilistic forecasts, well designed, data-driven *ex ante* assessments can help answer these concerns for particular contexts.

Credible evidence of acceptability and benefit to farmers may contribute to mobilizing funds and influencing the agendas of institutional partners. On the other hand, much of the support for forecast applications for agriculture has come from sources that do not traditionally fund agricultural research and development, and that have not yet demanded the level of evidence that traditional agricultural donors typically require.

(b) *Targeting interventions*
The potential to benefit from seasonal climate forecasts lies in the intersection of predictability of relevant components of climate variability, vulnerability (more correctly, sensitivity) to the adverse impacts of climate variability and ability to modify climate-sensitive decisions (Hansen 2002). *Ex ante* impact assessment, using integrated climate–crop–economic modelling, can provide a quantitative basis for selecting priorities

for allocating scarce resources among regions, farming systems and interventions. Examples of the use of *ex ante* modelling to target regions or populations seem to be absent from the climate applications literature. There are, however, a few examples of analysis that are relevant to setting priorities for forecast system development (Mjelde *et al.* 1997; Jones *et al.* 2000) and policy (Mjelde *et al.* 1996).

(c) *Ex ante* assessment and integrated modelling
Decision modelling within a value-of-information framework (Hilton 1981) has been the standard approach for estimating the potential value of advance climate information. A standard economic definition of the value of information is the expected value of the outcome of optimal decisions using the new information minus the expected value of outcome of optimal decisions based on the prior information

$$V_F = E\{U\Pi(\boldsymbol{x}^*|F;\Theta,\boldsymbol{e})\} - E\{U(\Pi(\boldsymbol{x}^*|\Theta;\Theta,\boldsymbol{e}))\},$$
(5.1)

where F is the information embodied in a forecast system, $U(\cdot)$ is a utility function that represents the subjective value associated with an outcome, Π is an economic outcome (e.g. income), $\boldsymbol{x}^*$ is the optimal value of a vector of relevant decisions, Θ is the prior information, and vector $\boldsymbol{e}$ represents the current state of all conditions besides information and decisions that influence outcomes. The prior information is generally assumed to be the historic climatology, although Sherrick *et al.* (2000) showed that this assumption may under-value forecast information due to farmers' biased perceptions of climatology.

The potential benefits of a forecast system for particular decisions can be estimated quantitatively by sampling hindcasts (i.e. past predictions) and climatic outcomes in a retrospective analysis. In the case of decisions related to production management or farmer livelihoods, this involves coupling climate prediction models, agricultural production models and economic resource accounting and decision models. In the relatively simple case of management of an individual crop with the goal of maximizing expected profit, forecast value can be estimated as

$$V_F \cong n^{-1} \sum_{i=1}^{n} (P_T y(\boldsymbol{x}^*|F_i; \theta_i, \boldsymbol{e}_T) - C_{\boldsymbol{x}^*|F_i})$$

$$- n^{-1} \sum_{i=1}^{n} (P_T y(\boldsymbol{x}^*|\Theta; \theta_i, \boldsymbol{e}_T) - C_{\boldsymbol{x}^*|\Theta}),$$
(5.2)

where y is crop yield, P is crop price, $C_{\boldsymbol{x}}$ is cost of production associated with management strategy $\boldsymbol{x}$, θ_i is observed weather in year i, T is the current year, and n is the number of hindcast years. For each hindcast year, crop yield is estimated as a function of observed weather and of management that is optimized for the hindcast. Net income is estimated with a simple enterprise budget, typically on a unit area basis.

Equation (5.2) is expressed in terms of forecasts of crop yields rather than seasonal climate anomalies because economic outcomes are a function of production outcomes and not climate, and because of the absence of any direct relationship between seasonal

climatic means and production response. Forecasts of crop yields can be derived from statistical production functions—historically the mainstay of *ex ante* modelling of the value of agricultural innovations—or from dynamic crop simulation models integrated with climate forecasts. Because they explicitly model the dynamic process underlying interactions, crop simulation models have the potential to provide more realistic and robust representation of the interactions between climate and management that are the source of value from seasonal forecasts, and reduce the accumulation of errors that result when yield is forecast as a statistical function of predicted seasonal climatic anomalies (Barrett 1998). A related argument is the practical difficulty of obtaining sufficient empirical data on crop×weather×management×soil interactions at the appropriate scale and across a sufficient range of variability to fit statistical production functions.

Estimating yield response, $y(\boldsymbol{x}, \theta, \boldsymbol{e})$, to management, observed weather and initial conditions is relatively straightforward. On the other hand, identifying optimal crop management $\boldsymbol{x}^*$ requires estimating yields for the range of management options under consideration for each hindcast. Because of the complex response surfaces that crop simulation models tend to produce, relatively slow but robust search algorithms must be used instead of the more efficient gradient search algorithms (Royce *et al.* 2001). Alternatively, a hybrid approach involving fitting a production function to simulated response to management, allows analytical solution by differentiation, but is limited to reasonably well behaved response surfaces of low dimensionality.

Farmers in various contexts have identified a fairly broad range of responses to seasonal forecast information beyond field-scale crop management (table 1). The general formulation (equation (5.1)) can be adapted to the farm level to handle decisions involving allocation of land and other scarce resources among crops and other enterprises or to account for risk and risk tolerance. Well developed farm planning methods can efficiently identify optimal allocation of resources, again under the assumptions of climatological information and forecast information.

Efforts to estimate the value of climate forecasts have relied heavily on decision modelling in a value-of-information framework. Based on developments in impact evaluation for other agricultural technologies, robust *ex ante* evaluation of the impacts of seasonal climate forecasts is likely to require and increasingly employ a wide range of quantitative and qualitative approaches (Thornton submitted).

6. FOSTERING AND GUIDING RESPONSES: MODELS FOR MANAGEMENT
(a) Modelling for agrotechnology transfer
Crop simulation was initially seen as a way to integrate knowledge of individual processes, obtain insights into interactions, and use predictive ability to test hypotheses. As their ability to simulate complex genotype× environment×management interactions advanced, crop models were increasingly seen as a way to enhance

Table 1. Potential farm decision responses to seasonal climate forecast information that farmers in Machakos and Makindu, Eastern Province, Kenya, identified during workshops (August 2004).
(The decision types represent the author's classification of farmer responses.)

type of decision	examples
intensification: quantities of productive resources used per unit land or labour	fertilizer use. Planting density. Pest management. Irrigation. Multiple cropping. Can include cultivar/seed selection
portfolio: resource allocation decisions	allocation of land among competing crops, farm enterprises, land uses. Allocation of household labour amount farm enterprises, off-farm enterprises, household care
asset exchanges and management	consumption versus precautionary savings versus investment. Borrowing, debt servicing. Leasing land. Procurement of resources, services. Precautionary maintenance. Storage
timing	timing of planting and other field operations. Timing of marketing. Forward contracts

the transferability of results of traditional agronomic research in the face of environmental heterogeneity.

The advances in food security and rural welfare associated with the green revolution in Asia and Latin America have been difficult to reproduce in marginal rainfed regions. Heterogeneity of the environment has been advanced as one explanation for low rates of adoption of improved technology, and weak returns on investment in extension services in Africa relative to other parts of the developing world. 'An important reason for the failure of earlier programmes was their top-down nature and limited recognition of the wide diversity and heterogeneity of farmers and fields as a prime characteristic of livelihoods and farming systems in (less-favoured areas)' (Kuyvenhoven *et al.* 2004).

Because the production outcomes of management are highly dependent on soils, climate and topography and on farmers' goals, assets, social status and access to markets and services, spatial heterogeneity of these variables creates a need to tailor management to local conditions (Byerlee 1987; Rhohrbach & Okwach 1999; Snapp *et al.* 2003). Experimental methodology developed in the crop sciences to control for the effects of variability in space and time, is not well suited to the task. Farming systems research (FSR), advanced as a way to understand the context-specific needs and opportunities of farmers, shares with agronomic experimentation the location specificity problem and need to aggregate to recommendation domains in order to scale up results, with an inevitable tradeoff between relevance and cost (Menz & Knipscheer 1981). The ten-year international benchmark sites network for agrotechnology transfer (IBSNAT) project was developed under the assumption that appropriate use of crop models could compensate for the limitations of traditional research methods in the face of environmental heterogeneity (IBSNAT 1993). Well validated process-oriented models were seen as relatively rapid and cost-effective means of transferring research results to locations other than where they were developed and tested, and tailoring technology to specific environments without having to replicate field research at every location.

The rationale for using system modelling for agrotechnology transfer in the face of environmental heterogeneity is relevant to the use of seasonal forecasts for climate risk management. Climate variability adds a time dimension to environmental heterogeneity.

Regionally adapted and tested crop models allow one to quickly explore the production outcomes of a range of management alternatives under a range of climate scenarios (realized or predicted), and for a range of soil conditions. System modelling is arguably the only tractable way to do so. Although agronomic trials can be replicated in space, at significant cost, to provide information on management outcomes across space, extending replicated trials over enough years to provide robust results across the range of climate variability is not feasible. Furthermore, adaptive climate risk management is not a packaged technology, but an information input with implications for potentially many aspects of the farming and livelihood system (table 1). Because of differences in resource endowment, goals, livelihood strategies and risk tolerance, these applications are likely to be more context-specific than many agronomic technologies.

(b) *Farm management decision support systems*
Although, modelling tools that came out of the IBSNAT project and similar efforts during the 1980s and early 1990s targeted researchers, the goal was to use models as '…the means by which knowledge of systems and their performance is made portable and accessible to users whose livelihood and welfare depend on this performance' (IBSNAT 1993). Yet, the mechanism for transferring the resulting knowledge to farmers was not always clear. Increased on-farm use of PCs in developed countries raised the prospect of developing model-based decision support systems (DSS) to deliver the benefits of modelling to farmers more directly through support of tactical farm management decisions.

There have been several attempts to develop and deliver agricultural simulation models via farmer DSS, primarily in Australia and the USA (McCown 2002). To address the problem of model complexity, most provide simplified user interfaces to crop models, or databases of pre-run simulations. PC-Yield addressed the data availability problem by packaging DSS software with a subscription to daily field-specific weather data updates via the Internet (Welch *et al.* 2002). The FARMSCAPE project provided on-site weather stations and soil characterization for client farmers (Carberry *et al.* 2002). Limited experience suggests that significant early and ongoing stakeholder participation is also a necessary condition for success (Carberry *et al.* 2002; McCown 2002; Welch *et al.* 2002).

Despite some modest successes, uptake of model-based farm DSS has, generally, been disappointing. A review of crop model applications in developing countries (Matthews & Stephens 2002) brought a growing awareness to the forefront, that crop simulation models have not fulfilled early expectations as a tool for transferring technology to farmers. From a review of 14 DSS projects, McCown (2002) provides a thoughtful analysis of reasons for the low level of farmer adoption, and suggests several niches where DSS might play a significant role in farm decision-making. One of the key lessons is that, while farmers might be willing to use a DSS as a tool to assist in low-level, routine tasks, they tend to resist any proxy—human or software—for their own management process. Two other observations about farm DSS are significant to this discussion. First, several authors have noted instances where interactions and experimentation around model-based DSS have challenged farmers' perceptions, and stimulated learning and the formulation of new heuristics (i.e. rules of thumb). Once the new heuristics are learned, the DSS is no longer needed. Second, there appears to be a trend toward delivering the knowledge embodied in model-based DSS through expert intermediaries, rather than directly to farmers via the software.

(c) *From decision support to discussion support*

The shift in focus away from the traditional notion of DSS toward the use of modelling to stimulate dialogue, highlight options and tradeoffs, and foster co-learning and consensus building lead to the relatively new notion of models as 'discussion support systems' (Meinke *et al.* 2001; Nelson *et al.* 2002; Bontkes & van Keulen 2003). 'In this 'mutual understanding' relationship, intervention intent shifts from educating and persuading to recognition of and respect for other ways of viewing the world....Intervention emphasis shifts from *prescribing* action to *facilitating* learning in actions' (McCown 2002). This transition in thinking about the role of agricultural simulation models parallels an ongoing shift within the broader agricultural development community away from a linear model of technology development and transfer, towards increasing recognition that farmers are not passive recipients but innovators who actively experiment and repackage technology to meet their needs and circumstances.

The farm DSS projects that McCown (2002) evaluated are all in developed countries. To what degree can this experience translate to smallholder farmers in developing countries? Limited experience suggests that the prospects are quite good. In a set of workshops with farmers in two villages in Zimbabwe, Carberry *et al.* (2004) used APSIM crop simulations as a basis for discussion about a range of farm management questions. Despite initial scepticism on the part of the research team and participating farmers, the farmers found the simulation results to be credible and relevant. The simulation model facilitated virtual experimentation, allowing researchers to respond quickly to questions that participating farmers raised about crop response to fertilizer, management of a limited supply of manure and impacts on competing crops of planting delays forced by labour shortage. The researchers concluded that the model facilitated a high level of farmer–researcher dialogue and debate between farmers, challenged farmers' perceptions in a manner that led to learning, and stimulated interest in on-farm testing of innovations proposed by the farmers. In the context of climate risk management, researchers used the APSIM model effectively with a group of farmers in western Tamil Nadu, India, as a basis for discussing and debating possible management responses to ENSO-based climate forecasts (Meinke *et al.* 2003; Selvaraju *et al.* submitted). Shifts in aggregate crop area statistics were consistent with farmer discussions about the 2002 climate forecast and crop model results. Gadgil *et al.* (2002) responded to a request from farmers by using the PNUTGRO model to evaluate climatic risk as a function of planting date for rainfed groundnut in southwestern Andhra Pradesh, India. The farmers appeared to value and learn from crop model results that supported a later planting date than normally recommended (Gadgil personal communication).

(d) *Model-based recommendations?*

Although, crop models have contributed significantly to discussions about climate applications between researchers and collaborating groups of farmers, the cost of such intensive interactions is high relative to the number of farmers impacted. I am aware of several researchers who are interested in using crop models as a basis for formulating advisories for broad distribution within farming communities. The trend in the USA and Australia towards use of crop models by expert intermediaries who advise farmers (McCown 2002) seems to support such an approach.

What are the prospects for agricultural research and extension services to routinely issue advisories based on integrated climate–crop models? I do not see enough evidence yet to fully answer this question. Because of the potential impacts of recommendations on farmer livelihoods and on the credibility of the provider, I favour a cautious approach. Accounting for the heterogeneity of soils and weather over a substantial area would be quite labour- and data-intensive. Yet, in the absence of such an effort, resulting recommendations would either suffer the same weakness identified for blanket fertilizer recommendations in heterogeneous rainfed environments (Rhohrbach & Okwach 1999; Snapp *et al.* 2003; Kuyvenhoven *et al.* 2004), or would need to be only partially specified, forcing farmers to refine them to suit their own circumstances (Reece & Sumberg 2003). Any such recommendations would require both substantial ground-truthing and support for some degree of farmer adaptation. Although, model-based analyses might be useful to guide a set of agronomic field experiments or a network of on-farm trials, these would need to be repeated in time to sample sufficient range of seasonal forecasts and realized weather to evaluate the robustness of recommendations.

Just as DSS have, in come cases, prompted learning and formulation of new heuristics that eliminated further need for the DSS among farmers (McCown 2002), it seems likely that crop models integrated with

seasonal forecasts may serve more as a vehicle researchers and farmer advisors to learn principles of climate risk management through accelerated experience and experimentation that they can then transfer through their interaction with farmers.

7. CONCLUSIONS

Integrated climate–crop models have the potential to make a genuine but limited contribution to the application of seasonal climate prediction to smallholder agriculture. I have highlighted three areas that appear to warrant continued effort: translating climate forecasts into more relevant information, providing *ex ante* evidence of benefits of advance information, and supporting efforts to improve management responses. The ease in which crop models can provide insights into the complex interactions between climate variations, management and crop response creates opportunities for learning that are not possible with other research approaches. On the other hand, this ease and flexibility carries the risk of overconfidence and misuse. The potential benefits that integrated climate–crop models offer can only be achieved if they are used appropriately, with understanding of their capabilities and limitations, and with cautious evaluation of model predictions and of the insights that arises from model-based decision analysis.

REFERENCES

Arndt, C. & Bacou, M. 2000 Economy wide effects of climate variability and prediction in Mozambique. *Am. J. Econ.* **82**, 750–754. (doi:10.1111/0002-9092.00074.)

Arndt, C., Bacou, M. & Cruz, A. 2003 Climate forecasts in Mozambique: an economic perspective. In *Coping with climate variability: the use of seasonal climate forecasts in Southern Africa* (ed. K. O'Brien & C. Vogel), pp. 129–152. Ashgate Studies in Environmental Policy and Practice. Abingdon, UK: Ashgate Publishing.

Baron, C., Sultan, B., Balme, M., Sarr, B., Traore, S., Lebel, T., Janicot, S. & Dingkuhna, M. 2005 From GCM grid cell to agricultural plot: scale issues affecting modelling of climate impact. *Phil. Trans. R. Soc. B* **360**, 2095–2108. (doi:10.1098/rstb.2005.1741.)

Barrett, C. B. 1998 The value of imperfect ENSO forecast information: discussion. *Am. J. Agr. Econ.* **80**, 1109–1112.

Barrett, C. B. 2003 Natural resources management in CGIAR. In *The CGIAR at 31: an independent meta-evaluation of the consultative group on international agricultural research* (ed. U. J. Lele), pp. 93–102. Washington, DC: The World Bank.

Binswanger, H. & Sillers, D. A. 1983 Technological priorities for farming in sub-Saharan Africa. *World Bank Res. Obs.* **3**, 81–98.

Blench, R. 1999 Seasonal climate forecasting: who can use it and how should it be disseminated? *Nat. Res. Perspect.* **47**, 1–5.

Bliss, C. J. & Stern, N. H. 1982 *Palanpur: the economy of an Indian village.* Oxford, UK: Clarendon Press.

Bontkes, T. S. & van Keulen, H. 2003 Modelling the dynamics of agricultural development at farm and regional level. *Agr. Syst.* **76**, 379–396. (doi:10.1016/S0308-521X(02)00128-2.)

Broad, K. & Agrawala, S. 2000 The Ethiopia food crisis—uses and limits of climate forecasts. *Science* **289**, 1693–1694.

Byerlee, D. 1987 From adaptive research to farmer recommendations and extension advice. *Agr. Admin. Ext.* **27**, 231–244.

Cane, M. A., Eshel, G. & Buckland, R. W. 1994 Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. *Nature* **16**, 3059–3071.

Cantelaube, P. & Terres, J. 2005 Seasonal weather forecasts for crop yield modeling in Europe. *Tellus* **57A**, 476–487.

Carberry, P. S. *et al.* 2002 The FARMSCAPE approach to decision support: farmers', advisers', researchers' monitoring, simulation, communication and performance evaluation. *Agr. Syst.* **74**, 141–177. (doi:10.1016/S0308-521X(02)00025-2.)

Carberry, P., Gladwin, C. & Twomlow, S. 2004 Linking simulation modelling to participatory research in smallholder farming systems. In *Modelling nutrient management in tropical cropping systems* (ed. R. J. Delve & M. E. Probert), pp. 32–46. AICR Proceedings No. 114. Canberra: Australian Centre for International Agricultural Research.

Childs, I. R. W., Hastings, P. A. & Auliciems, A. 1991 The acceptance of long-range weather forecasts: a question of perception? *Aust. Meteorol. Mag.* **39**, 105–112.

Dercon, S. 2002 Income risk, coping strategies, and safety nets. *World Bank Res. Obs.* **17**, 141–166. (doi:10.1093/wbro/17.2.141.)

Dercon, S. 2004 Growth and shocks: evidence from rural Ethiopia. *J. Dev. Econ.* **74**, 309–329. (doi:10.1016/j.jdeveco.2004.01.001.)

Dilley, M. 1997 Climatic factors affecting annual maize yields in the valley of Oaxaca, Mexico. *Int. J. Climatol.* **17**, 1549–1557. (doi:10.1002/(SICI)1097-0088(19971130) 17:14<1549::AID-JOC208>3.0.CO;2-N.)

Dilley, M. & Boudreau, T. 2001 Coming to terms with vulnerability: a critique of the food security definition. *Food Policy* **26**, 229–247. (doi:10.1016/S0306-9192(00) 00046-4.)

Eakin, H. 2000 Small holder maize production and climate risk: a case study from Mexico. *Climatic Change* **45**, 19–36. (doi:10.1023/A:1005628631627.)

Elbers, C., Gunning, J. W. & Kinsey, B. 2003 Growth and risk: methodology and micro evidence. Tinbergen Institute Discussion Paper TI 2003-068/2. Amsterdam: Tinbergen Institute, Vrije Universiteit. (available online at http://econwpa.wustl.edu/eps/dev/papers/0408/0408014.pdf .)

Ericksen, P. 2004 Report of the first food security outlook forum for the greater horn of Africa, held in conjunction with the 14th greater horn of Africa climate outlook forum (GHACOF 14) August 25–26, 2004 Nairobi, Kenya, p. 34. Palisades, New York: International Research Institute for Climate Prediction.

Gadgil, S., Rao, P. R. S. & Rao, K. N. 2002 Use of climate information for farm-level decision making: rainfed groundnut in southern India. *Agr. Syst.* **74**, 431–457. (doi:10.1016/S0308-521X(02)00049-5.)

Goddard, L., Mason, S. J., Zebiak, S. E., Ropelewski, C. F., Basher, R. & Cane, M. A. 2001 Current approaches to seasonal to interannual climate predictions. *Int. J. Climatol.* **21**, 1111–1152. (doi:10.1002/joc.636.)

Gong, X., Barnston, A. & Ward, M. 2003 The effect of spatial aggregation on the skill of seasonal precipitation forecasts. *J. Clim.* **16**, 3059–3071. (doi:10.1175/1520-0442(2003) 016<3059:TEOSAO>2.0.CO;2.)

Haile, M. 2005 Weather patterns, food security and humanitarian responses in Sub-Saharan Africa. *Phil. Trans. R. Soc. B* **360**, 2169–2182. (doi:10.1098/rstb. 2005.1746.)

Hallstrom, D. G. 2004 Interannual climate variation, climate prediction, and agricultural trade: the costs of surprise versus variability. *Rev. Int. Econ.* **12**, 441–455. (doi:10. 1111/j.1467-9396.2004.00460.x.)

Hammer, G. L. 2000 Applying seasonal climate forecasts in agricultural and natural ecosystems: a synthesis. In *Applications of seasonal climate forecasting in agricultural and natural ecosystems: the Australian experience* (ed. G. L. Hammer, N. Nicholls & C. Mitchell), pp. 453–462. Atmospheric and Oceanographic Sciences Library Volume 21. Dordrecht, The Netherlands: Kluwer Academic Publishers.

Hansen, J. 2002 Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. *Agr. Syst.* **74**, 309–330. (doi:10.1016/S0308-521X(02)00043-4.)

Hansen, J. W. 2004 Can smallholder farmers benefit from seasonal climate forecasts? In *New directions for a diverse planet: Proceedings for the 4th International Crop Science Congress, Brisbane, Australia, 26 September-1 October 2004* (ed. T. Fischer, N. Turner, J. Angus, L. McIntyre, M. Robertson, A. Borrell & D. Lloyd). Gosford, Australia: The Regional Institute Ltd. (Published online at http://www.regional.org.au/.)

Hansen, J. W. & Indeje, M. 2004 Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. *Agr. Forest Meteorol.* **125**, 143–157. (doi:10.1016/j.agrformet.2004.02.006.)

Hansen, J. W., Potgieter, A. & Tippet, M. 2004 Using a general circulation model to forecast regional wheat yields in Northeast Australia. *Agr. Forest Meteorol.* **127**, 77–92. (doi:10.1016/j.agrformet.2004.07.005.)

Hansen, J. W., Dilley, M., Goddard, L., Ebrahimian, E. & Ericksen, P. Submitted*a*. Climate variability and the millennium development goal hunger target. *Food Policy.*

Hansen, J. W., Ines, A., Challinor, A., Wheeler, T. & Moron, V. Submitted*b*. Translating climate forecasts into agricultural terms: advances and challenges. *Clim. Res.*

Hilton, R. W. 1981 The determinants of information value: synthesizing some general results. *Manage. Sci.* **27**, 57–64.

Hulme, M., Biot, Y., Borton, J., Buchanan-Smith, M., Davies, S., Folland, C., Nichols, N., Seddon, D. & Ward, N. 1992 Seasonal rainfall forecasting for Africa part II—application and impact assessment. *Int. J. Environ. Stud.* **40**, 103–121.

IBSNAT (International Benchmark Sites Network for Agrotechnology Transfer) 1993 *The IBSNAT Decade.* Honolulu: Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii.

Ingram, K. T., Roncoli, M. C. & Kirshen, P. H. 2002 Opportunities and constraints for farmers of west Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. *Agr. Syst.* **74**, 331–349. (doi:10.1016/S0308-521X(02)00044-6.)

Jochec, K. G., Mjelde, J. W., Lee, A. C. & Conner, J. R. 2001 Use of seasonal climate forecasts in rangeland-based livestock operations in West Texas. *J. Appl. Meteorol.* **40**, 1629–1639. (doi:10.1175/1520-0450(2001)040<1629:UOSCFI>2.0.CO;2.)

Jones, J. W., Hansen, J. W., Royce, F. S. & Messina, C. D. 2000 Potential benefits of climate forecasting to agriculture. *Agr. Ecosyst. Environ.* **82**, 169–184. (doi:10.1016/S0167-8809(00)00225-5.)

Kuyvenhoven, A., Ruben, R. & Pender, J. 2004 Editorial: development strategies for less-favoured areas. *Food Policy* **29**, 295–302. (doi:10.1016/j.foodpol.2004.08.001.)

Letson, D., Llovet, I., Podesta, G., Royce, F., Brescia, V., Lema, D. & Parellada, G. 2001 User perspectives of climate forecasts: crop producers in Pergamino, Argentina. *Clim. Res.* **19**, 57–67.

Luseno, W. K., McPeak, J. G., Barrett, C. B., Little, P. D. & Gebru, G. 2003 Assessing the value of climate forecast information for pastoralists: evidence from southern Ethiopia and northern Kenya. *World Dev.* **31**, 1477–1494. (doi:10.1016/S0305-750X(03)00113-X.)

Matthews, R. & Stephens, W. (eds) 2002 *Crop-soil simulation models: applications in developing countries.* Wallingford, UK: CAB International.

McCown, R. L. 2002 Changing systems for supporting farmers' decisions: problems, paradigms, and prospects. *Agr. Syst.* **74**, 179–220. (doi:10.1016/S0308-521X(02)00026-4.)

Meinke, H., Baethgen, W. E., Carberry, P. S., Donatelli, M., Hammer, G. L., Selvaraju, R. & Stöckle, C. 2001 Increasing profits and reducing risks in crop production using participatory systems simulation approaches. *Agr. Syst.* **70**, 493–513. (doi:10.1016/S0308-521X(01)00057-9.)

Meinke, H., Howden, S. M., Baethgen, W., Hammer, G. L., Selvaraju, R. & Stone, R. C. 2003 *Can climate knowledge lead to better rural policies and risk management practices?* Paper presented at Insights and Tools for Adaptation: Learning from Climate Variability workshop, National Oceanographic and Atmospheric Association, Washington, DC, 18–20 November 2003. (Published online at http://www.climateadaptation.net/docs/papers/meinke.pdf.)

Menz, K. M. & Knipscheer, H. C. 1981 The location-specificity problem in farming systems research. *Agr. Syst.* **7**, 95–103. (doi:10.1016/0308-521X(81)90033-0.)

Mjelde, J. W., Thompson, T. N. & Nixon, C. J. 1996 Government institutional effects on the value of seasonal climate forecasts. *Am. J. Agric. Economics* **78**, 175–188.

Mjelde, J. W., Thompson, T. N., Nixon, C. J. & Lamb, P. J. 1997 Utilising a farm-level decision model to help prioritise future climate prediction research needs. *Meteorological Appl.* **4**, 161–170.

Motha, R. P. & Heddinghaus, T. R. 1986 The joint agricultural weather facility's operational assessment program. *Bull. Am. Meteor. Soc.* **67**, 1114–1122. (doi:10.1175/1520-0477(1986)067<1114:TJAWFO>2.0.CO;2.)

Nelson, D. & Finan, T. 2000 The emergence of a climate anthropology in Northeast Brazil. *Practicing Anthropol.* **22**, 6–10.

Nelson, R. A., Holzworth, D. P., Hammer, G. L. & Hayman, P. T. 2002 Infusing the use of seasonal climate forecasting into crop management practice in North East Australia using discussion support software. *Agr. Syst.* **74**, 393–414. (doi:10.1016/S0308-521X(02)00047-1.)

Ngugi, R. K. 2002 Climate forecast information: the status, needs and expectations among smallholder agro-pastoralists in Machakos District, Kenya. IRI Technical Report 02-04. New York: International Research Institute for Climate Prediction, Palisades.

O'Brien, K., Sygna, L., Næss, L. O., Kingamlono, R. & Hochobeb, B. 2000 Is information enough? User responses to seasonal climate forecasts in Southern Africa. CICERO Report 2000:3. Oslo: Center for International Climate and Environmental Research.

Patt, A. G. & Gwata, C. 2002 Effective seasonal climate forecasts applications: examining constraints for subsistence farmers in Zimbabwe. *Global Environ. Change Hum. Policy Dimensions* **12**, 185–195.

Phillips, J. 2003 Determinants of forecast use among communal farmers in Zimbabwe. In *Coping with climate variability: the use of seasonal climate forecasts in Southern Africa* (ed. K. O'Brien & C. Vogel), pp. 110–126. Ashgate Studies in Environmental Policy and Practice. Abingdon, UK: Ashgate Publishing.

Phillips, J. & McIntyre, B. 2000 ENSO and interannual rainfall variability in Uganda: implications for agricultural

management. *Int. J. Climatol.* **20**, 171–182. (doi:10.1002/(SICI)1097-0088(200002)20:2<171::AID-JOC471>3.0.CO;2-O.)

Phillips, J. G., Unganai, L. & Makaudze, E. 2001 Current and potential use of seasonal climate forecasts for resource-poor farmers in Zimbabwe. In *Impacts of El Niño and climate variability on agriculture.* (ed. C. Rosenzweig, K. J. Boote, S. Hollinger, A. Iglesias & J. Phillips), pp. 87–100. ASA special publication no. 63. Madison, WI: American Society of Agronomy.

Reece, D. & Sumberg, J. 2003 More clients, less resources: towards a new conceptual framework for agricultural research in marginal areas. *Technovation* **23**, 409–421. (doi:10.1016/S0166-4972(01)00122-5.)

Rhohrbach, D. D. & Okwach, G. E. 1999 Setting targets: modeling crop performance or cropping decisions. In *Risk management for maize farmers in drought-prone areas of southern Africa.* Proceedings of a workshop held at Kadoma Ranch, Zimbabwe, 1–3 October 1997. (Available online at http://www.cimmyt.cgiar.org/worldwide/CIMMYT_Regions/CIMMYT_Africa/RiskMngtKadoma/RiskMgntKadoma.pdf .)

Rosenzweig, C. 1994 Maize suffers a sea-change. *Nature* **370**, 175–176. (doi:10.1038/370175a0.)

Rosenzweig, M. R. & Binswanger, H. P. 1993 Wealth, weather risk and the composition and profitability of agricultural investments. *Econ. J.* **103**, 56–78.

Royce, F. S., Jones, J. W. & Hansen, J. W. 2001 Model-based optimization of crop management for climate forecast applications. *Trans. Am. Soc. Agr. Eng.* **44**, 1319–1327.

Sanchez, P. A. 2002 Soil fertility and hunger in Africa. *Science* **295**, 2019–2020. (doi:10.1126/science.1065256.)

Sanchez, P., Izac, A. M., Buresh, R., Shepherd, K., Soule, M., Mokwunye, U., Palm, C., Woomer, P. & Nderitu, C. 1997 Soil fertility replenishment in Africa as an investment in natural resource capital. In *Replenishing soil fertility in Africa* (ed. R. Buresh & P. Sanchez), pp. 1–46. SSSA Special Publication No. 51. Madison, WI: Soil Science Society of America.

Selvaraju, R., Meinke, H. & Hansen, J. W. Submitted. Management responses to seasonal climate forecasts in southern India's dryland cropping systems. *Agr. Syst.*

Sherrick, B. J., Sonka, S. T., Lamb, P. J. & Mazzocco, M. A. 2000 Decision-maker expectations and the value of climate prediction information: conceptual considerations and preliminary evidence. *Meteorol. Appl.* **7**, 377–386. (doi:10.1017/S1350482700001584.)

Snapp, S. S., Blanke, M. J. & Donovan, C. 2003 Realigning research and extension to focus on farmers' constraints and opportunities. *Food Policy* **28**, 349–363. (doi:10.1016/j.foodpol.2003.08.002.)

Stephens, D. J., Butler, D. G. & Hammer, G. L. 2000 Using seasonal climate forecasts in forecasting the Australian wheat crop. In *Applications of seasonal climate forecasting in agricultural and natural ecosystems: the Australian experience* (ed. G. L. Hammer, N. Nicholls & C. Mitchell), pp. 351–366. Atmospheric and Oceanographic Sciences Library, Volume 21. Dordrecht, The Netherlands: Kluwer Academic Publishers

Stoorvogel, J. J. & Smaling, E. M. A. 1990 Assessment of soil nutrient depletion in sub-Saharan Africa, 1983–2000, p. 125. Report No. 28. Wageningen, The Netherlands: Winand Staring Center for Integrated Land, Soil and Water Research (SC-DLO).

Tarhule, A. & Lamb, P. J. 2003 Climate research and seasonal forecasting for West Africans. *Bull. Am. Meteorol. Soc.* **84**, 1741–1759. (doi:10.1175/BAMS-84-12-1741.)

Thornton, P. K. Submitted. *Ex ante* impact assessment and seasonal climate forecasts: status and issues. *Clim. Res.*

Verdin, J. & Klaver, R. 2002 Grid-cell-based crop water accounting for the famine early warning system. *Hydrol. Processes* **16**, 1617–1630. (doi:10.1002/hyp.1025.)

Vogel, C. 2000 Useable science: an assessment of long-term seasonal forecasts amongst farmers in rural areas of South Africa. *S. Afr. Geogr. J.* **82**, 107–116.

Walker, T. S. 1991 Improved technology in relation to other options for dealing with climatic risk to crop production in the semiarid tropics. In *Climate risk in crop production: models and management for the semiarid tropics and subtropics* (ed. R. C. Muchow & J. A. Bellamy), pp. 511–525. Walingford: CAB International.

Welch, S., Jones, J., Brennan, M., Reeder, G. & Jacobson, B. 2002 PCYield: model-based decision support for soybean production. *Agr. Syst.* **74**, 79–98. (doi:10.1016/S0308-521X(02)00022-7.)

Ziervogel, G. 2004 Targeting seasonal climate forecasts for integration into household level decisions: the case of small farmers in Lesotho. *Geogr. J.* **170**, 6–21. (doi:10.1111/j.0016-7398.2004.05002.x.)

Zimmerman, F. J. & Carter, M. R. 2003 Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *J. Dev. Econ.* **71**, 233–260. (doi:10.1016/S0304-3878(03)00028-2.)