Economic Value of Seasonal Climate Forecasts for Agriculture: Review of Ex-Ante Assessments and Recommendations for Future Research

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(Manuscript received 17 July 2006, in final form 3 October 2007)

ABSTRACT

Advanced information in the form of seasonal climate forecasts has the potential to improve farmers' decision making, leading to increases in farm profits. Interdisciplinary initiatives seeking to understand and exploit the potential benefits of seasonal forecasts for agriculture have produced a number of quantitative ex-ante assessments of the economic value of seasonal climate forecasts. The realism, robustness, and credibility of such assessments become increasingly important as efforts shift from basic research toward applied research and implementation. This paper surveys published evidence about the economic value of seasonal climate forecasts for agriculture, characterizing the agricultural systems, approaches followed, and scales of analysis. The climate forecast valuation literature has contributed insights into the influence of forecast characteristics, risk attitudes, insurance, policy, and the scale of adoption on the value of forecasts. Key innovations in the more recent literature include explicit treatment of the uncertainty of forecast value estimates, incorporation of elicited management responses into bioeconomic modeling, and treatment of environmental impacts, in addition to financial outcomes of forecast response. It is argued that the picture of the value of seasonal forecasts for agriculture is still incomplete and often biased, in part because of significant gaps in published valuation research. Key gaps include sampling of a narrow range of farming systems and locations, incorporation of an overly restricted set of potential management responses, failure to consider forecast responses that could lead to "regime shifts," and failure to incorporate state-of-the-art developments in seasonal forecasting. This paper concludes with six recommendations to enhance the realism, robustness, and credibility of ex-ante valuation of seasonal climate forecasts.

1. Introduction

The year-to-year variability of the climate is a serious challenge for agriculture. Beyond its direct impacts on production and market prices, the uncertainty associated with climate variability is a challenge to management, as farmers must make many critical, climate-sensitive decisions months before the impacts of climate are realized. Climate variability imposes costs on farmers predominantly through two different mechanisms, the first primarily driven by information constraints in production decisions and the second by the burden that uncertainty imposes on risk-averse optimizers. In the first case, climate variability creates a moving target for management. That is, when a farmer must make management decision before the climate variables are known for a particular year, the farmer must make decisions that are an optimal compromise for the full set of possibilities as opposed to an optimal solution for the particular year that will be actually experienced. The moving-target effect can lead to losses for both risk-neutral and risk-averse farmers.

Second, because risk-averse farmers directly experience disutility from variation in returns, risk imposes an additional burden on this group. This cost can be manifested through protective production strategies that sacrifice some portion of average income due to climate uncertainty in order to reduce the variability of returns. In interpreting impacts specifically related to risk aversion, it is important to note not that risk aversion itself is necessarily undesirable, as it may well stem from important and rational concerns, but rather that the risk imposes an additional burden on risk-averse farmers.

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DOI: 10.1175/2007JAMC1540.1

Opportunities for the use of seasonal climate forecasts arise in situations in which there is a combination of climatic predictability, system response, and decision capacity (Hansen 2002). In those cases, climate forecasts can increase farmers' preparedness and lead to better economic and environmental outcomes in the long run. A skillful climate forecast reduces uncertainty by reducing the spread of possible outcomes for the upcoming season relative to the climatological distribution, and by conveying shifts in the central tendency of climatic outcomes. This information allows farmers to better adapt management decisions to upcoming weather conditions, thereby attenuating the moving-target problem; and, because uncertainty has been reduced, it allows risk-averse farmers to relax the additional protective strategies in climatically favorable or average seasons that they would use to stabilize returns.

Because seasonal climate forecasts may have an impact on farmers' welfare, both qualitative and quantitative assessments are important to fully exploit the potential benefits associated with them (value) and to understand the limitations of their application (use). Ex-ante valuation seeks to assess the potential benefits of an innovation in advance of its adoption, while ex-post valuation seeks to assess actual outcomes following adoption. Although seasonal forecasts have been issued routinely for more than two decades in parts of the world, their effective dissemination and systematic use to manage climate risk in agriculture represent a new innovation relative to most other agricultural technologies—in most cases too new for reliable ex-post assessment of value.[1] Ex-ante assessment of the value of seasonal forecasts serves two related roles (Thornton 2006). First, it provides the evidence needed to mobilize funds and influence the agendas of institutional partners in the face of competing priorities. Second, it provides insights that inform targeting of effort (e.g., farming systems, locations, forecast characteristics, and decision support tools) where the net benefits are likely to be greatest.

The substantial body of research on the value of seasonal climate forecasts for agriculture makes use of both quantitative economic valuation and a range of qualitative social science approaches to understand determinants of use and value. Quantitative studies have generally employed an ex-ante bioeconomic modeling approach to estimate the value of forecast information for particular decisions in particular contexts. A review by Wilks (1997) describes several characteristics of prescriptive decision studies, proposes a classification scheme, and presents examples of forecast value assessments with emphasis on weather forecasts. Hill and Mjelde (2002) provide a broader review with estimates of forecast value at farm and aggregated levels, and consider other sectors such as disaster control and recreation. They also list ongoing research efforts to apply seasonal climate forecasts and discuss constraints for the adoption of seasonal climate forecasts. Rubas et al. (2006) point out opportunities to improve our understanding of the economics of information by going beyond existing modeling approaches, incorporating methods such as game theory and mechanism design theory to assess the value of seasonal climate forecasts in a broader range of decision settings. Following their argument regarding the need for innovative and rigorous research, our purpose is to survey published evidence about the economic value of seasonal climate forecasts for agriculture, discuss limitations of past studies, and propose avenues for improving the realism and robustness of future assessments of forecast value.

2. Conceptual and methodological framework

The quantitative, ex-ante forecast valuation studies surveyed here represent a subset of a more diverse body of research on the value of seasonal forecasts, which in turn is part of the broader field of the economics of information. A range of social science methods (e.g., surveys and ethnographic and participatory research) have been employed to address more qualitative questions about whether forecasts have value and what factors determine farmers' ability to use and benefit from forecasts; and, more recently, approaches to overcoming barriers related primarily to communication and understanding of forecast information have been explored. Much of this research was initiated in response to the 1997/98 El Niño event, and targeted smallholder farming systems in developing countries. This research has demonstrated a high degree of interest in and range of potential responses to forecast information; and provides rich insights into cultural, cognitive, economic, institutional, and policy factors that can constrain or enhance the value of advance climate information. Roncoli (2006) provides an excellent review of much of this literature.

a. The cost of climatic uncertainty

Understanding how climate variability impacts agricultural decision making provides a basis for anticipat-

[1] By "ex-post assessment," we mean empirical assessment of the value of a forecast system after implementation and widespread adoption. For either ex-ante or ex-post valuation studies, the decision problem is ex-ante in the sense that decisions must be made prior to encountering uncertain states of nature that affect decision outcomes.

ing the mechanisms by which advance climate information in the form of seasonal forecasts may benefit agriculture. Climate variability presents a moving target for management, because "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). Because a producer does not know the specific climate condition outcomes that will occur in a given year, the farmer must take seasonal management actions that are a compromise spanning all of the possible situations. If a farmer selects management that maximizes profit averaged among the range of weather outcomes (for the moment assuming indifference to risk), the management that is optimum on average will be far from optimum in most individual years. Although there are few quantitative estimates of the resulting loss of income, it appears to be substantial. From the results of a model-based optimization study of maize fertilizer and planting density management, assuming both perfect foreknowledge of weather conditions and knowledge of the historic climatological distribution (Jones et al. 2000), climatic uncertainty costs the profit-maximizing farmer in Pergamino, Argentina, on average 23.4% of gross margin. This uncertainty reduces the efficiency of nitrogen (N) fertilizer use by 38.9%, from 131.5 down to 80.4 kg grain (kg N)$^{-1}$. While in the same study the cost of uncertainty was lower (19.3% of average gross margin) in Tifton, Georgia, it is likely higher in regions with higher climate-induced production variability.

If extremely low levels of income are particularly undesirable for a farmer, this implies that the farmer is risk-averse. Because many farmers are averse to risk, there is an additional burden caused by climatic uncertainty beyond the costs due only to the "moving target" effect. In the face of climatic uncertainty, it is worthwhile for risk-averse farmers to employ a range of protective strategies that sacrifice average income and marginal productivity of assets in order to buffer returns against climatic extremes. Farmers' ex-ante responses to risk include avoidance of improved production technology (Kebede 1992; Marra et al. 2003; Abadi Ghadim et al. 2005), selection of less risky but less profitable crops or cultivars (Dercon 1996; J. Morduch 1990, personal communication), underuse of fertilizers (Bliss and Stern 1982, chapter 8; Binswanger and Pingali 1983), and shifting from productive to nonproductive but more liquid assets as precautionary savings (Paxon 1992; Zimmerman and Carter 2003; Fafchamps 2003). A more risk-averse farmer is less able to take advantage of favorable or average years because management must be oriented toward protecting the farmer from bad years. Although it is worthwhile for risk-averse farmers to sacrifice average productivity to protect themselves from low incomes, the literature shows that the cost of such ex-ante risk management responses can be substantial, and is greater for those who are relatively poor and hence least able to tolerate risk. Econometric analyses in villages in peninsular India estimated that management responses to a unit standard deviation increase in climatic variability reduced average farm profits by 15% for farmers in the median wealth class, and by 35% for farmers in the lowest quartile of wealth (Rosenzweig and Binswanger 1993). Zimmerman and Carter (2003) estimated that relatively poor farmers in six villages in Burkina Faso forego about 18% of their income to buffer against the existing level of risk (attributed primarily to climate variability), primarily by maintaining precautionary stores of grain, while the relatively wealthy farmers in the sample forego only 0.4% of income.

A poverty trap implies the existence of some threshold level of assets below which individuals are unable to accumulate the necessary resources to escape poverty without external intervention. Ongoing research into poverty traps (e.g., Barrett 2005; Carter and Barrett 2006) suggests that climate variability is one of several factors that cause farmer livelihood trajectories to bifurcate around a poverty trap threshold, and keep many locked in persistent poverty. Severe or repeated climate shocks can push households into poverty by forcing them to divest productive assets (Dercon 2004). Climatic uncertainty contributes to reduced average income by prompting more conservative, low-risk, low-return asset portfolios and livelihood strategies than would be worthwhile if the uncertainty were not present. Because tolerance to risk tends to increase with increasing resource endowment (Binswanger 1981; Pope and Just 1991), returns per unit of productive asset also decrease at low levels of assets—a necessary condition for the existence of a microeconomic poverty trap (Carter and Barrett 2006). Finally, by reducing both the willingness of poor households to invest resources that might be needed to buffer against future shocks (Paxon 1992; Zimmerman and Carter 2003) and the willingness of lenders to supply credit to poor households, climate variability limits access to the capital needed to overcome entry barriers into more profitable enterprises.

b. The value of information

Two seminal works formalizing the economic value of climate-related information to an agent are Nelson and Winter (1964) and Hilton (1981), which lay out the basic conceptual framework that most of the literature follows. The assessment of the economic value of climate information relies on two primary assumptions. First, the agents are fully aware of the consequences of all possible combinations of decisions and states of the world (i.e., economic performances conditioned on selected alternatives and realizations of the climate). Second, the agents are rational decision makers. In other words, they will choose the alternative or combination of alternatives that maximizes their utility function, which is the result of the outcome of the system and their individual values and risk perceptions.

The agent is faced with an ex-ante optimization problem. That is, the agent must make the input decision prior to knowing the climate outcome. In this optimization, the problem is to select the optimal level of input using probabilistic information about potential climate outcomes. For each possible realization of the climate state and management alternative, there will be a potentially unique realization of the utility function. The optimal management strategy (e.g., sowing date, plant density, land allocation, or fertilizer level) will be one that maximizes the expected utility (i.e., the probability-weighted utility function whose weights are given by the relative frequency of the unconditional states of the climate).

The statement above can be expressed mathematically in the following way. Let $U[Y(\mathbf{X}, \mathbf{C}), W_0]$ be the utility function of a decision maker as a function of the profits (Y) received after performing an agricultural activity in the current growing season. The shape of the utility function depends on the decision maker's risk aversion and her (his) initial wealth (W_0). The parameter Y is a function of both the vector of decisions $\mathbf{X}$ (i.e., a vector containing the combination of the production factors) and the vector $\mathbf{C}$ that contains the combinations of meteorological variables for the growing season. Because the agent faces climate uncertainty, the vector $\mathbf{C}$ is a random variable whose multivariate probability density function is given by $f(\mathbf{C})$.

The expected utility for each agricultural activity is given by

$$E\{U[Y(\mathbf{X}), W_0]\} = \int U[Y(\mathbf{X}, \mathbf{C}), W_0]f(\mathbf{C})\, d\mathbf{C}. \quad (1)$$

Under this situation, the farmer will choose a combination of management production decisions ($\mathbf{X}^*$) such that

$$\max_X E\{U[Y(\mathbf{X}), W_0]\} = E\{U[Y(\mathbf{X}^*), W_0]\}. \quad (2)$$

Following each particular draw, the climate outcome ($\mathbf{C}$) is revealed, and the agent experiences the results of agricultural production based on the input levels chosen in the ex-ante optimization process, given the particular realization of $\mathbf{C}$, or $U[Y(\mathbf{X}^*, \mathbf{C}), W_0]$. If the agent had perfect information, the agent could have selected optimal input levels better suited for the realization of the vector $\mathbf{C}$, selecting $\mathbf{X}‡$ that maximizes the nonstochastic $U[Y(\mathbf{X}‡, \mathbf{C}), W_0]$. However, since $\mathbf{C}$ is a random variable, the optimal ex-ante input choice $\mathbf{X}^*$ is not necessarily the input choice that would have been appropriate for the particular realization of C. Thus, there are income and utility losses due to inputs being set at the imperfect information levels $\mathbf{X}^*$ as opposed to the perfect information levels $\mathbf{X}‡$.

Typically, it is assumed that the agent's future meteorological conditions are consistent with the historic climatological distribution when there is no forecast available. Instead of representing the distribution of all historical climatological outcomes, a skillful climate forecast represents a distribution weighted toward the particular draw likely to be experienced in the coming season. In many cases when ENSO states are used, the forecast is typically the distribution representing the particular subset of climatological events that occurred during the particular ENSO state.

If the decision maker has access to a seasonal climate forecast (F) containing a different assessment about the likelihood of future climate conditions $f(\mathbf{C}|F)$, then her (his) objective function will be to maximize the expected utility function using the conditioned probability density function on the available forecast. The solution of this conceptual problem will be a vector of decisions ($\mathbf{X}†$) that satisfies the condition

$$\max_X E\{U[Y(\mathbf{X})|F, W_0]\} = E\{U[Y(\mathbf{X}†)|F, W_0]\}. \quad (3)$$

Therefore, the climate forecast allows the agent to select a vector of inputs that are more likely to be well suited to the climate vector that will be experienced. The benefits of the forecast are that the agent faces less uncertainty and can make more effective input choices than when using the climatology distribution information.

Phrased in terms of the ex-ante decision maker's problem, the value of information is the expected value of forecast information (EVOI). The EVOI is the value that the decision agent would have for the forecast in an ex-ante optimization, that is, the difference between the expected utility when using the forecast distribution in ex-ante input decision making and the expected utility from using the climatological distribution (Hilton 1981), expressed as

$$\text{EVOI} = E\{U[Y(\mathbf{X}†), W_0]\} - E\{U[Y(\mathbf{X}^*), W_0]\} \quad (4)$$

(Katz and Murphy 1997).

This measure, in utility units, is typically mapped into a cash value either by directly subtracting the expected profits, for an agent that behaves as a risk-neutral profit-maximizing firm (e.g., Nelson and Winter 1964; Messina et al. 1999; Mjelde and Hill 1999), or, for the risk-averse agent, by subtracting the certainty equivalents of the profit distributions (e.g., Hilton 1981; Mjelde et al. 1996; Letson et al. 2005). The certainty equivalent is the monetary value that would give a risk-averse optimizer the same amount of utility as the probabilistic distribution of potential income expected. The resulting value of information of the seasonal climate forecast can be interpreted as the amount of money that the decision maker is willing to trade off for a forecast that reduces uncertainty in realized income. Because of the potential for different risk tolerances, the value for two otherwise identical farmers can be different even though the actual additional monetary returns received at the end of the growing season from following the climate forecasts are equal.

c. *Seasonal climate forecasts*

There is a rich body of literature in the field of seasonal climate forecasts, including sources of predictability, skill and forecast uncertainty, forecasting methods, and future directions. In this subsection, we present a summary of key elements within the context of assessment of the value of seasonal climate forecast for agriculture. Useful reviews are found in Cane (2001), Goddard et al. (2001), and Palmer et al. (2005).

Because the atmosphere is chaotic, categorical forecasts (i.e., forecasts in which only one of the set of possible events will occur) are possible from knowledge of the initial atmospheric state only up to about 10–14 days. However, boundary forcing from the underlying ocean and land surfaces influences climate anomalies and evolves more slowly than weather systems, thereby allowing some degree of predictability. An example of these boundary forces is the well-known coupled atmospheric–oceanic El Niño–Southern Oscillation (ENSO) phenomenon. Knowledge of the state of ENSO shifts the probabilities associated with climate anomalies in one direction or another when there is a statistical association between ENSO-related sea surface temperature anomalies (SSTA) and climate anomalies (Barnston et al. 2000). Given the persistence of SSTA for several months, this association provides the basis for a simple seasonal climate forecast system.

Several climate prediction centers produce operational forecasts by running general circulation models (GCMs). These models numerically simulate the dynamics of the atmosphere and calculate fluctuations in climate that result from slow changes in boundary forcing. Because the resolution is usually coarse, postprocessing is required to dynamically or statistically downscale the results for each grid cell to obtain forecasts for specific locations. The dispersion of results among ensembles of multiple GCM simulations, run with different initial atmospheric conditions, provides a probabilistic measure of the likelihood of future climatic conditions.

d. *Crop simulation models*

Inspired by the successes of system analysis and simulation, biologists and agronomists have applied similar techniques to evaluate the response of agricultural systems to different external forces. One of the approaches has been the mathematical representation of crop growth and development, with the aim of estimating crop productivity as a function of weather and soil conditions as well as of crop management. There are a wide variety of models, ranging from empirical–statistical models to models based on physiological processes. Hoogenboom (2000) classifies the uses of crop simulation models into (i) strategic applications, where models are run to compare crop management scenarios as decision support systems; (ii) tactical applications, where the runs are made using current weather conditions to help producers make management decisions during the growing season; and (iii) forecasting applications, which provide insights about future crop yield outcomes.

Crop simulation models that are run with realizations of growing season weather that represent a seasonal forecast allow agricultural scientists to evaluate the most suitable management alternatives based on the distribution of yield outcomes. Hansen et al. (2006) review methods for coupling crop models with seasonal climate forecasts.

3. Seasonal forecast valuation literature

We considered 33 papers that report quantitative and comparable estimates of the economic value of seasonal climate forecasts. Because some of the studies include more than one crop or location, the number of different assessments is 58. The assessments include three different levels of analysis. The most common is the enterprise level, where the value of seasonal climate forecasts is obtained as a function of changes in management for an individual crop. Other studies (Messina et al. 1999; Jones et al. 2000; Letson et al. 2005) estimate the value of climate forecasts at the farm level considering land allocation. Studies (Adams et al. 1995, 2003; Solow et al. 1998; Chen et al. 2002; Hill et al. 2004) that use equilibrium models to estimate the value of seasonal climate information at an aggregate scale are able to model price response to changing supply and demand and to provide estimates of consumer and producer surplus as a measure of the benefits to society, and are capable of representing trade and storage.

The majority of studies focused on annual crops (maize, wheat, soybean, sorghum, potato, and sunflower) grown under rainfed conditions. Intensity of production (fertilizer, insecticide, and herbicide use; degree of mechanization) is generally high, representing commercial agriculture. None of the studies considered subsistence agriculture. A few considered irrigated horticultural crops. Only two studies addressed livestock operations (Bowman et al. 1995; Jochec et al. 2001).

Almost all studies consider a discrete type of forecast. ENSO-based forecasts, in which the phases of the event are foreseen (El Niño, La Niña, normal, or phases of the Southern Oscillation), are the most frequent. Other studies consider discrete forecasts for tercile categories of seasonal total precipitation (Mjelde et al. 1997a,b) and only few studies are based on theoretical representations of forecast accuracy (Abedullah and Pandey 1998; Mjelde et al. 1997a,b). The use of discrete categories simplifies the assessment of the expected economic value of climate information, because the relative frequencies of the forecasted events can be easily computed from historical records. The potential benefits are evaluated, generating series of weather years conditioned on the forecast such as historical analogs, synthetic series obtained from weather generators, or monthly totals. Climatic events are usually translated into crop yield outcomes using crop simulation models run under a wide variety of management alternatives. Maximization criteria are used to choose optimal alternatives.

a. *Estimates of value*

Table 1 synthesizes the results reported for the expected economic value of climate forecasts. In addition to the estimate in U.S. dollars (USD) per hectare, Table 1 includes a column highlighting the main features investigated or factors considered that influence the value of climate forecasts. Some studies calculate benefits of climate information at aggregated levels by means of equilibrium models and then compute consumer and producer surplus (Adams et al. 1995, 2003; Chen et al. 2001, 2002; Mjelde et al. 2000; Solow et al. 1998). In order to facilitate comparison of estimates of value in those situations, even though it may introduce some bias, the reported figures were divided by the total area of crops in the region (information obtained from agricultural census or regional statistics). The decisions investigated were grouped into production management (e.g., sowing date, plant density, fertilizer level), and land allocation decisions. A few considered the effect of government policies or insurance on the value of climate forecasts

Although each case represents a particular assessment (dependent on the nature of the system under study, the methodologies, the assumptions made, and the type of seasonal climate forecast investigated), the additional economic returns per hectare within a commodity category (i.e., rainfed agronomic crops or irrigated horticultural crops) generally varied within an order of magnitude. As a group, cereals exhibit the lowest economic values. The value of climate forecasts can be severely affected by price–cost relationships (e.g., Messina et al. 1999; Jones et al. 2000; Letson et al. 2005; Meza and Wilks 2004), and must be considered when assessing the benefits of seasonal climate information.

While the values reported in Table 1 are expected values averaged among all years, because of the nature of the forecasting systems most of the monetary benefit comes from a small set of growing seasons where farmers substantially adjust their management either to exploit particularly favorable climatic conditions or to avoid unnecessary losses in particularly adverse conditions. For example, for the potato crop at Valdivia, Chile, Meza and Wilks (2003) found that the value of information reached 320 USD ha^{-1} in the warm ENSO phase, but was zero for the neutral and cold phases.

b. *Innovations and contributions*

Forecast valuation studies have employed a number of innovations and have provided a wealth of insights about factors that influence forecast value.

1) Forecast characteristics

Several of the earlier studies focused on how forecast characteristics influence value, with a view to informing improvements in seasonal forecasts (Sonka et al. 1987; Mjelde et al. 1988, 1993; Mazzocco et al. 1992). Mjelde et al. (1988) demonstrated the trade-off between forecast accuracy and lead time for sequential decisions. A study of relationships between forecast value and quality measures such as entropy and variance concluded that the relationship between value and any particular measure of forecast quality is generally not monotonic (Mjelde et al. 1993). Hill et al. (2000, 2004) and Chen et al. (2002) compared the value of 3-phase ENSO forecasts with a 5-phase forecast system based on the

Southern Oscillation index. However, comparisons of analog forecast systems with differing numbers of categories are problematic unless precautions are taken to control for the artificial skill that tends to increase as the number of categories increases (Hansen et al. 2006).

2) Risk attitudes and information value

Although Hilton (1981) demonstrated that there is no general monotonic relationship between risk aversion and the value of information, empirical evidence found in this work (Messina et al. 1999; Jones et al. 2000; Meza et al. 2003; Letson et al. 2005) suggests that forecast value tends to increase when moving from a risk-neutral to a slightly risk-averse decision maker, but is likely to decrease at very high levels of risk aversion, since highly protective risk management strategies constrain the decision set. In other words, a highly risk-averse farmer may not be able to bear the risk of the uncertainty in the forecast itself. Illustrative land allocation optimization results for Pilar, Argentina (Fig. 1a), based on the methods and assumptions in Messina et al. (1999), are consistent with published studies. Letson et al. (2005) demonstrated that price volatility is also a significant source of farm risk, and should be incorporated into analyses in order to estimate forecast value accurately under risk aversion.

Studies of forecast value under varying degrees of risk aversion have provided useful insights. For example, different tails of the forecast distribution can be more valuable to different types of decision makers (Meza and Wilks 2003; Letson et al. 2005). Letson et al. (2005) observed that forecasts of climatic adverse conditions were most valuable to nearly risk-neutral farmers, while forecasts of favorable conditions became more valuable at increasing risk aversion. This finding is somewhat counterintuitive, since risk aversion implies that farmers are particularly concerned with adverse conditions. The intuition behind the higher relative value of forecasts of favorable conditions for more risk-averse farmers is that these farmers tend to manage all years using low return, protective strategies, in case any year turns out to be an extremely bad year. Thus, a forecast that enables the farmer to relax conservative strategies in favorable years allows the farmers to take advantage of the favorable years while retaining very protective strategies when adverse years are anticipated. While there is not sufficient evidence to generalize this result, it is consistent with the findings of Messina et al. (1999) and with our own experience (see Fig. 1b). Hansen and Selvaraju (2001) used forecast value expressed on a certainty equivalent basis, estimated from a simple farm land allocation model for southern India, to demonstrate how biased perception or communication of the uncertainty associated with seasonal forecasts can reduce or negate the value of probabilistic seasonal forecasts to risk-averse farmers.

3) Interactions with insurance and policy

Forecasts and insurance are complimentary risk management tools. Forecasts allow mitigation to address predictable risks while insurance provides protection against what is not predictable. When combined, insurance can be used to increase the utility of forecasts, allowing a risk-averse producer to make management decisions based on probabilistic forecast information that would have too much uncertainty to act upon without insurance (Carriquiry and Osgood 2007). If the insurance is not priced using forecast information, it is important that insurance transactions be carried out before forecasts have skill. Otherwise, clients can behave strategically and undermine the insurance financing (Hess and Syroka 2005; World Bank 2005; Luo et al. 1994; Ker and McGowan 2000). Government programs and policies, such as subsidized insurance, restrictions on crops or areas, and various tax schemes, have consequences for the use of forecast information in agriculture, with impacts depending on the particulars of the programs (Cabrera et al. 2007; Mjelde et al. 1996; Mjelde and Hill 1999).

4) Market impacts and scale of adoption

Because of market equilibrium, large-scale changes in land allocation or crop management in response to widespread adoption of seasonal forecasts could have substantial impact on commodity prices and hence on farmer income. The forecast valuation literature can be grouped broadly into field- and farm-scale studies that assume that the scale of adoption is so small that market impacts can be ignored, and studies at an aggregate scale that assume complete adoption and incorporate market impacts through economic equilibrium modeling (Table 1). Two notable exceptions are Messina et al. (2006) and Rubas et al. (2008). In the first study, the authors modeled the value of ENSO information for tomato growers in Florida as a function of the scale of adoption. They showed that the information has a high potential value for the first farmers who use it, but that the value decreases because of reduced equilibrium market prices as more farmers adopt forecasts. With 100% adoption, forecasts have negative value to producers if they act independently, but producers can retain substantial value if they coordinate their responses to forecasts optimally. Rubas et al. (2008) examined the adoption of the use of seasonal climate forecasts in multiple countries throughout an international wheat trade

TABLE 1. Expected economic value of seasonal climate forecast for different agricultural systems.

Country	Location	Crop*	Decision**	EVOI (USD ha^{-1})	Forecast type	Sensitivity to	Comments/contributions	Reference
Argentina	Pergamino	Mz	P	15	ENSO phase	Consensus management	A decision map for maize production was built and then discussed with experts	Bert et al. (2006)
Argentina	Pergamino	Mz, Wh, So, Su	LA	12	ENSO phase	Price variability, risk aversion	Forecast value is a random variable that depends on crop prices	Letson et al. (2005)
Argentina	Pergamino	Mz, Wh, So, Su	LA	11	ENSO phase	Risk aversion, prices, initial wealth	Crop mix also varied with prices and initial soil moisture	Messina et al. (1999)
Argentina	Pergamino	Mz	P	15.1	ENSO phase		Provides an estimate of the upper limit of the value of forecasts simulating perfect knowledge of daily weather over the next growing season	Jones et al. (2000)
Argentina	Pergamino	Mz	P	25.8	Rainfall terciles			Jones et al. (2000)
Argentina	Pergamino	So, Mz, Pn, Wh	LA	15	ENSO phase	Risk aversion, prices, initial wealth		Jones et al. (2000)
Argentina	Pergamino	Mz	P	8.2	ENSO phase		Uses simulated annealing algorithm with Decision Support System for Agrotechnology Transfer (DSSAT) model to search the solution space and apply it to climate management decisions	Royce et al. (2001)
Argentina	Pergamino	Mz	P	5.2	ENSO phase		Information of crop management was collected during interviews with end-users	Royce (2002)
Argentina	Pilar	Mz, Wh, So, Su	LA	35	ENSO phase	Risk aversion, prices, initial wealth		Messina et al. (1999)
Australia	Dalby	Sr, Co, Fal	Rot	31	SOI 5 phases			Carberry et al. (2000)
Australia	Goondiwindi	Wh	P	5	SOI 5 phases	Risk of loss	Compares the cumulative probability distribution of profit for fixed and SOI-based strategies	Hammer et al. (1996)
Australia	Queensland	Wh	P	3.5	SOI 3 phase	Risk aversion	Uses a sequential decision model composed by three mathematical programs	Marshall et al. (1996)

TABLE 1. (*Continued*)

Country	Location	Crop*	Decision**	EVOI (USD ha^{-1})	Forecast type	Sensitivity to	Comments/contributions	Reference
Australia	Merredin region	Wh, Lp, Pa	WFO	1.23	SOI 5 phases		Uses a whole-farm discrete stochastic programming model	Petersen and Frasier (2001)
Australia	Murray-Darling Basin	Co	LA	3	SOI 5 phases	Risk aversion	SOI information is used to forecast streamflows and water supply for next growing season	Ritchie et al. (2004)
Canada	Manitoba	SWh	P	3.84	SOI 3 phase		Compares different SOI-based forecast methods	Hill et al. (2000)
Canada	Manitoba	SWh	P	2.13	SOI 3 phase			Hill et al. (2000)
Canada	Alberta	SWh	P	0.55	SOI 3 phase			Hill et al. (2000)
Chile	Concepcion	Po	P	45	ENSO phase	Risk aversion	Provides a method to judge whether EVOI assessments are statistically different from zero	Meza et al. (2003)
Chile	Concepcion	SWh	P	10	ENSO phase	Risk aversion		Meza et al. (2003)
Chile	Temuco	Po	P	110	ENSO phase	Risk aversion		Meza et al. (2003)
Chile	Temuco	SWh	P	30	ENSO phase	Risk aversion		Meza et al. (2003)
Chile	Valdivia	WWh	P	28	ENSO phase	Risk aversion		Meza et al. (2003)
Chile	Valdivia	Po	P	120	ENSO phase	Risk aversion		Meza et al. (2003)
Costa Rica	Guanacaste	Ri	P	49.1	ENSO phase			Royce (2002)
Mexico	Country level	Several	P	10.1	ENSO phase		Estimates are derived from an economic model that calculates production and consumption changes as a function of yield changes during each ENSO phase	Adams et al. (2003)
Mexico	Santa Julia	Mz	P	11.3	ENSO phase			Royce (2002)
Philippines	Victoria	Ri	P, Lb	5.5	Seasonal total, rainfall terciles	Risk aversion	Uses mathematical programming where hired labor is included as decision variable	Abedullah and Pandey (1998)
United States	Country level	Several	P	0.74	ENSO phase	Imperfect/perfect forecasts	One of the first studies calculating forecast value at aggregated levels	Adams et al. (1995)
United States	Jackson Co., FL	Pn, Mz, Co	LA	2.9	ENSO phase	Federal policies/risk aversion	The inclusion of commodity loan programs and crop insurance programs reduce the value of climate information	Cabrera et al. (2007)
United States	Country level	Several	P	2.2	ENSO phase		Estimates changes in forecast value as a result of shifts in ENSO frequency and intensity	Chen et al. (2001)
United States	Country level	Several	P	2.01	ENSO Phase	Number of ENSO phases	Calculates additional benefits derived from alternative 5-phase definition	Chen et al. (2002)

TABLE 1. (*Continued*)

Country	Location	Crop*	Decision**	EVOI (USD ha^{-1})	Forecast type	Sensitivity to	Comments/contributions	Reference
United States	Tifton, GA	Mz	P	7	ENSO phase		Also analyses historical yield ratios for 10 different crops in 8 states	Hansen et al. (2001)
United States	Tifton	WWh	P	4.4	ENSO phase			Hansen et al. (2001)
United States	Illinois	WWh	P	0	SOI 3 phase			Hill et al. (2000)
United States	Kansas	WWh	P	1.09	SOI 3 phase			Hill et al. (2000)
United States	Ohio	WWh	P	0	SOI 3 phase			Hill et al. (2000)
United States	Oklahoma	WWh	P	3.58	SOI 3 phase			Hill et al. (2000)
United States	Texas	WWh	P	1.22	SOI 3 phase			Hill et al. (2000)
United States	Washington	WWh	P	1.55	SOI 3 phase			Hill et al. (2000)
United States	South Dakota	SWh	P	2.24	SOI 3 phase			Hill et al. (2000)
United States	North Dakota	SWh	P	0.93	SOI 3 phase			Hill et al. (2000)
United States	Montana	SWh	P	0.94	SOI 3 phase			Hill et al. (2000)
United States	Texas	Livestock	R/D	0.89	Analog years	Prices	Uses focus groups to analyze decision concerning stocking–destocking	Jochec et al. (2001)
United States	Tifton	Mz	P	13	ENSO phase			Jones et al. (2000)
United States	Tifton	Mz	P	16.7	Rainfall terciles			Jones et al. (2000)
United States	Tifton	So, Mz, Pn, Wh	LA	3	ENSO phase	Risk aversion/prices/ initial wealth		Jones et al. (2000)
United States	Northern plains	Wh	Rot	10	Seasonal precipitation		Sequential decisions Moisture carryover influences next growing season outcomes	Katz et al. (1987)
United States	Southern Florida	To	P + H + M	700	ENSO phase	Forecast adoption/ cooperative use	Links tomato production to aggregated supply and prices	Messina et al. (2006)
United States	Illinois	Mz	P	2.2	Forecast of 5 classes	Forecast quality	Shows how producers can benefit from improving forecast quality for poorer conditions	Mjelde et al. (1993)
United States	Texas	Sr + Mz	P + FP	34	Tercile		Federal programs can increase the value of seasonal climate forecasts by eliminating some constraints. Crop Insurance decrease the value of seasonal climate forecasts	Mjelde and Hill (1999)
United States	Texas	Mz	P	4.3	SOI 3 phase	Forecast quality	Uses ordinary least squares regression model	Mjelde et al. (1997a)

Table 1. (*Continued*)

Country	Location	Crop*	Decision**	EVOI (USD ha^{-1})	Forecast type	Sensitivity to	Comments/contributions	Reference
United States	Texas	Sr	P	0.6	SOI 3 phase	Forecast quality		Mjelde et al. (1997a)
United States	Champaign, IL	Mz	P	46.5	Seasonal total	Forecast accuracy/lead time	There is a trade-off between forecast accuracy and lead time	Mjelde et al. (1988)
United States	Texas	Sr + Mz	WFO	33	Tercile		Disaster programs decreases the value of improved climate forecasts	Mjelde et al. (1996)
United States	Texas	Sr	P	3	SOI 3 phase	Decision set	All decision types must be modeled to value seasonal forecasts	Mjelde et al. (1997b)
United States	Corn Belt	Mz	P	12.5	Tercile	Sequence of "good," "bad" years	Uses an equilibrium model linked to a decision model and calculates expected present value changes in net surplus	Mjelde et al. (2000)
United States	United States	Several	P	1.57	ENSO phase	Forecast skill	Economic value of seasonal climate forecasts is measured by the increase in social welfare	Solow et al. (1998)
United States	North and South Dakota	Mz, Wh	Rot	1.4	Seasonal temperature and precipitation	Forecast quality	Contour quality/value relationships as a function of forecast variance	Wilks and Murphy (1986)

* Co = Cotton; Gn = Groundnut; Mz = Maize; Pn = Peanut; Po = Potato; So = Soybean; Sr = Sorghum; Su = Sunflower; Ri = Rice; Wh = Wheat.
** LA = Land allocation; Lb = Labor; P = Production; P + FP = Production and Federal Programs; WFO = Whole farm optimization; R/D = Restocking–Destocking; Rot = Rotation; P + H + M = Production, Harvest and Marketing.

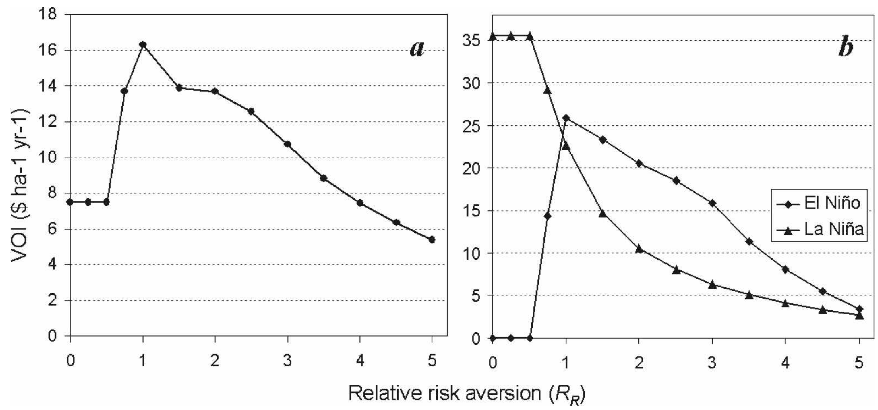

FIG. 1. Value of ENSO phase information for farm land allocation averaged (a) across years and (b) in favorable (El Niño) and adverse (La Niña) climatic years, as a function of increasing coefficient of relative risk aversion, for Pilar, Argentina. Assumptions and methods are described in Messina et al. (1999).

model. These authors also found that early adopters benefit the most, and that after 60%–95% adoption there is no further incentive for producers to incorporate seasonal climate forecasts in their production system.

5) Stability of forecast value

Forecast value [Eq. (4)] is defined by integrating across expected and realized states of nature [Eq. (1)] with and without forecasts. In practice, forecast valuation involves sampling a particular subperiod of hindcasts and historic weather realizations, and potentially other stochastic drivers such as prices. Several forecast valuation studies have looked at sensitivity to prices (Messina et al. 1999; Jones et al. 2000; Meza and Wilks 2004) and to different sampled sets of years (Mjelde et al. 2000). Letson et al. (2005) proposed that the value of seasonal climate forecast should be treated as a random variable rather than a unique figure. Using stochastic weather and price models, they generated estimates of forecast value distributions.

6) Incorporation of elicited or observed management responses

While most of the studies considered a narrow range of decisions with little or no evidence that they are relevant or feasible from the standpoint of farmers, two attempted to model decisions that were elicited from participating farmers. Jochec et al. (2001) used focus groups of ranchers in western Texas to elicit factors that influence stocking rate decisions. They modeled the benefits of seasonal forecasts for stocking rate decisions and involved ranchers in evaluating the results, but did not use the process to explore a wider set of management responses. Bert et al. (2006) incorporated maize management responses to ENSO-based forecasts, elicited from farmer advisors in the Pampas region of Argentina, into model-based analysis of forecast value, and compared the results with profit-maximizing strategies.

7) Environmental externalities

Although most studies have expressed forecast value only in terms of production, income, or cost savings, a few have also considered environmental impacts of agricultural management practices. Hill et al. (1999) showed that the use of Southern Oscillation information provides producers with a method for using nitrogen more efficiently with positive environmental consequences. Mavromatis et al. (2002) showed the potential to increase groundnut yields and reduce nitrate leaching into groundwater in northern Florida by adjusting planting dates based on ENSO phase. Although they did not look at income, increased yields are expected to increase income proportionally, as adjusting planting date alone has no apparent financial cost. Cabrera et al. (2005, 2006) examined the use of climate forecast information to develop management strategies that minimize nitrogen leaching while maintaining or increasing farm profits.

c. *Gaps*

Realism and credibility become increasingly important as efforts to assess the value of seasonal forecasts move from basic research toward applied goals like evidence for resource mobilization and insight for targeting interventions. Furthermore, substantial international investment in climate monitoring infrastructure and prediction institutions increasingly requires evidence of global rather than local benefits. Research on the value of seasonal climate forecasts for agriculture has provided many useful insights, but has not yet matured to the point of meeting the growing need for comprehensive, realistic, credible, quantifiable assessment of benefits that can motivate and guide intervention. We argue that several gaps in the literature have contributed to an incomplete and often biased picture of the value of seasonal climate forecasts for agriculture.

1) RANGE OF FARMING SYSTEMS AND LOCATIONS

Our ability to target development of climate forecast services where the expected benefit is greatest is constrained by the limited sample of farming systems and locations represented within the body of forecast valuation literature. Furthermore, the quantitative valuation literature is likely to give a pessimistic picture of the potential value of seasonal forecasts because it underrepresents farming systems and locations where high predictability, high sensitivity to climatic variability, or high value of production favor high forecast value.

Published quantitative assessments of seasonal forecasts value have targeted a limited set of farming systems and commodities (Fig. 2a) in a few countries (United States, Canada, Mexico, Argentina, Costa Rica, Chile, Australia, and the Philippines) that generally have well-developed, market-oriented agriculture. While the Philippines might be considered an exception, the irrigated rice production system that Abedullah and Pandey (1998) evaluated is managed quite intensively. Most published quantitative studies to date have focused on rainfed agronomic crops in a limited set of high-potential agricultural regions. We argue that the body of quantitative forecast valuation literature does not give a realistic picture of the value of seasonal forecasts because of its limited representation of farming systems and locations.

Factors that favor forecast value include the value of production, sensitivity of farming systems to climate variability, predictability, and flexibility to adjust management in response to information. Published quantitative studies are not available for the parts of the globe—Northeast Brazil, much of Indonesia and southern Philippines, the central Pacific Islands, parts of East Africa—that show the highest current predictability of precipitation at a seasonal lead time.

The highest published value of ENSO-based seasonal forecasts per unit area is for a high-value horticultural crop (tomatoes; Messina et al. 2006). Forecast value estimates are generally higher for the few irrigated horticultural crops represented than for rainfed agronomic crops (Fig. 2b). Additional horticultural crops, livestock systems, and irrigated agriculture warrant serious consideration before we can make robust generalizations about the value of climate forecasts.

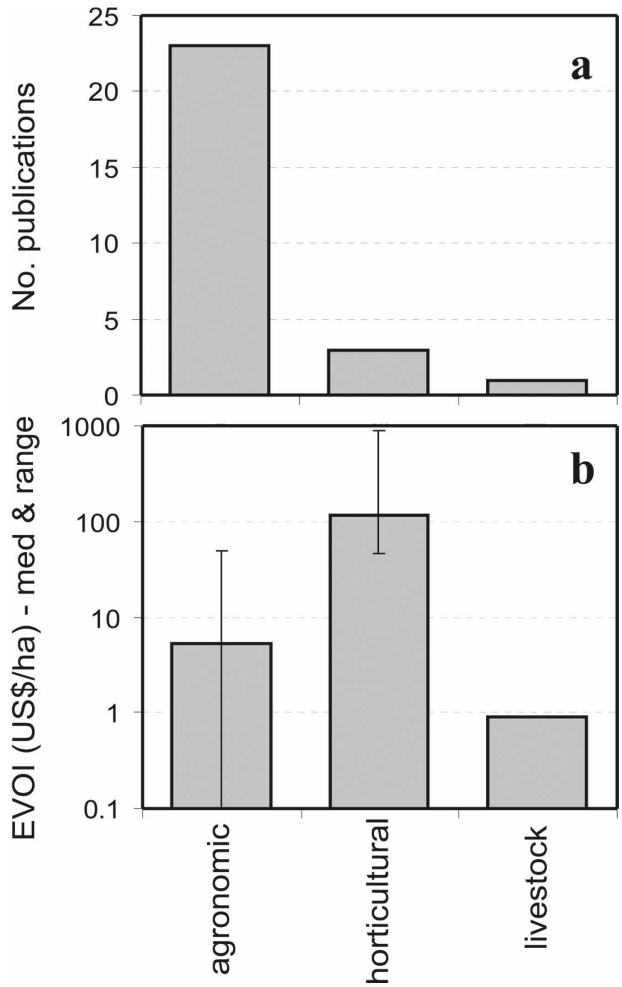

FIG. 2. (a) Number of published assessments and (b) range of estimates of seasonal forecasts' value for different farming systems.

All other things being equal, the value of forecast information is expected to be greater where agriculture is more sensitive to climate fluctuations (Hansen 2002; Meza et al. 2003). Climate variability is generally the dominant source of risk and a major impediment to development in smallholder rainfed farming systems in dryer (i.e., subhumid to arid) regions of the tropics. Barrett (1998) argued that relatively poor smallholder farmers in these regions should obtain the greatest benefit from seasonal forecasts because of their insurance value, if impediments can be overcome. A substantial amount of effort has gone into exploring the potential for smallholder rainfed farmers in developing countries to benefit from seasonal forecasts and understanding determinants of use and value, yet quantitative assessments of forecast value are virtually absent.

2) Limited choice set

Mjelde et al. (1997b) argued and demonstrated that evaluating only a few types of farm decisions will lead to underestimation of seasonal climate forecasts. Interactions with farmers have identified a rich variety of promising production and livelihood decision responses to seasonal climate forecasts, particularly in smallholder farming systems in developing countries (e.g., Everingham et al. 2002; Ingram et al. 2002; Ngugi 2002; Tarhule and Lamb 2003; Ziervogel 2004). Yet quantitative valuation studies have generally targeted a quite limited subset of potential management responses.

The majority of the studies we surveyed focused on agronomic management practices (Table 1). Several modeled land allocation among crops (Messina et al. 1999; Jones et al. 2000; Ritchie et al. 2004; Cabrera et al. 2007). Only a few (Mjelde et al. 1997b; Hill et al. 2004; Letson et al. 2005) considered both agronomic management and land allocation among crops. The modeling approaches employed align well with the decisions considered. It is not clear, however, whether the salient decision options determine the modeling tools used, or whether the ease with which available tools represent particular climate-sensitive decisions (e.g., crop models for agronomic decisions, linear or nonlinear programming for land allocation) may influence the decision responses considered. There are very few instances in which elicited or observed decision responses are cited as the basis for the decisions considered.

The tendency for EVOI to increase with at least the first increments of risk aversion in several of these studies suggests that ignoring risk aversion where it is present can lead to undervaluation of forecast information. This, in turn, suggests that evaluating the entire farm may improve assessments even when management of a single enterprise is considered, as economic risk cannot be evaluated or managed at the enterprise level because of the imperfect covariance among enterprises.

The practices of integrating quantitative valuation studies with qualitative, farmer-participatory research approaches (e.g., surveys, focus groups, ethnographic research) to elicit a fuller set of promising management responses and employing bioeconomic modeling approaches that are rich enough to capture the salient responses and characteristics of the system that impinge on those decisions would greatly improve our understanding of the value of seasonal forecasts to agriculture.

3) Poverty traps and regime shifts

The seasonal forecast valuation literature focuses on incremental changes to decisions that farmers make routinely on an annual basis. Yet our understanding of how risk impacts smallholder agriculture raises the prospect that effective management of climate risk might contribute to more fundamental changes in the farming system—“regime shifts”—that could move poor farmers onto a different livelihood trajectory. The notion of regime shifts between multiple stable equilibria comes from ecology (e.g., Scheffer et al. 2001) and builds on the seminal work of Holling (1973). Research into poverty traps shows that the livelihoods of farmers can also exhibit multiple stable equilibria that cause livelihoods to bifurcate around a poverty trap threshold level of initial assets.

If advance climate information could help farmers who are trapped in poverty to transition into more productive technology, more profitable enterprises, and qualitatively different livelihood trajectories, the benefits would be quite substantial. We suggest three ways this might happen. First, holding precautionary reserves of nonproductive liquid assets at the expense of investing in productive assets is a common strategy to protect against the possibility of crop failure and food shortfall associated with adverse weather. A forecast of favorable climatic conditions could provide incentive to invest a portion of these reserves into productivity-increasing or income-generating assets. Second, risk aversion in the face of climatic risk is often cited as one of the reasons for generally poor adoption of improved technology in high-risk rainfed regions. By favoring high returns through more intensive technology and by reducing the risk of losing any initial cash outlay, a forecast of favorable climatic conditions might provide incentive to adopt or at least experiment with new technology. Third, the reduction in risk and potential increase in demand that can be anticipated in climatically favorable years might prompt input and credit markets, which can be averse to risk, to expand services to high-risk farmers in these low-risk seasons. In all three cases, the cumulative effect over several favorable seasons might stimulate a transition from persistent poverty to a pathway toward asset accumulation and increased productivity and profitability.

The prospect that seasonal climate forecasts might contribute to such regime shifts has not yet received much research attention, and remains speculative. Any quantitative study of this question would need to go beyond the simple single-period decision models typical of forecast valuation studies and consider long-term dynamic effects on productive assets and technology adoption. Elbers et al. (2007) touched on this question. Using a multiperiod model of wealth accumulation parameterized with rural household data from Zimbabwe, they attributed approximately one-third of a simulated 46% reduction in 50-yr wealth accumulation to ex-post losses associated with climate and other fluctuations, and the remaining two thirds to ex-ante responses to associated uncertainties that in principle could be mitigated if they were anticipated. Bharwani et al. (2005) used a dynamic, multiagent-based simulation model to show how seasonal climate forecasts might impact wealth accumulation and long-term economic viability for interacting sets of relatively poor and better-off farmers in the province of Limpopo, South Africa.

4) Climate prediction "state of the art"

Depending on the objectives, forecast valuation could legitimately target either current operational forecasts or the best forecast system that is feasible with current technology. The categorical indicators of ENSO or hypothetical probability shifts of tercile categories that characterize the forecast valuation literature do not, in general, represent the best predictions that climate science has to offer. They do not, for example, consider any predictability associated with the intensity, timing, or other characteristics of ENSO events; nor do they account for any predictability associated with the other tropical ocean basins or land surfaces. Statistical climate prediction models have generally approached their predictive limits. The accuracy of forecast systems based on dynamical, physically based models of the global climate system sometimes exceeds that of the best statistical models, and is expected to grow with improvements in models, data assimilation, computer capacity, and postprocessing methods (Cane 2001). In those locations and seasons where dynamic climate forecast models outperform categorical ENSO indicators, failure to incorporate the best climate science would tend to underestimate forecast value. Although there is some relevant work in progress, we have not seen any published assessments of value to agriculture of forecasts that are based on dynamic climate models.

On the other hand, uncritical use of either forecasts from historic analogs or multivariate statistical methods raises the risk of artificial skill (Hansen et al. 2006) and overestimation of forecast value (Robinson and Butler 2002). The danger of overstating forecast value increases as the number of forecast categories increases and number of years within each category decreases, but can be controlled to some degree by applying appropriately conservative statistical methods such as cross-validation. Although there is some risk of undervaluing seasonal forecasts by failing to incorporate the best available methods for modeling crops, forage, or hydrology in response to predicted climate fluctuations, the greater danger appears to be overvaluing seasonal forecasts by using simulated results as a proxy for actual impacts without adjusting for model error.

4. Seasonal climate forecasts and agriculture: Are we there yet?

Important advances have been made in the last decades both in our understanding of the physics and dynamics of the atmosphere and our ability to model them. These scientific achievements have enabled operational production and dissemination of climate forecasts that are skillful at a seasonal lead time, and they have prompted efforts to capture the potential value of that information for agriculture and other sectors.

There are good theoretical arguments for expecting seasonal forecasts to be valuable for agriculture. The ex-ante economic valuation studies that we reviewed suggest that the value is generally positive but modest as a proportion of average income or value of production. Yet the value of seasonal forecasts to agriculture is still the subject of considerable controversy. This is particularly true for marginal rainfed farming regions of the tropics where vulnerability to climate risk is greatest. Several factors contribute to the difficulty of synthesizing generalizations about the value of seasonal forecasts from published research. First, studies of smallholder farming systems in tropical regions have tended to employ qualitative approaches to understand determinants of use and value, while quantitative economic modeling studies have tended to target high-potential regions in more developed countries. Few studies have taken advantage of the complementary strengths of quantitative and qualitative methods for assessing value. Second, quantitative forecast valuation studies have sampled a range of farming systems and locations that is too narrow to support robust generalizations. Third, the forecast valuation literature has so far failed to incorporate the best forecast methods that climate science currently has to offer, to consider all of the salient management responses, and to account for all of the mechanisms of benefit, particularly those associated with regime shifts.

Resolving the uncertainty about the value of seasonal climate prediction to agriculture requires rigorous expost impact studies, after forecasts have been widely communicated and supported adequately for a long enough period to allow learning, adaptation, and widespread adoption. In the meantime, we propose that several feasible enhancements will improve the reliability of our overall picture of the value of seasonal forecasts. We can

- expand the range of farming systems and locations, with particular emphasis on (i) regions that are known to have high seasonal predictability, (ii) smallholder rainfed agriculture in high-risk regions, and (iii) high-value agriculture;
- combine the more qualitative social science methods for understanding the determinants of information use and value with bioeconomic modeling approaches that are rich enough to incorporate the resulting knowledge realistically;
- include all salient management response options;
- account more completely for the mechanisms of benefit, particularly those involving regime shifts;
- incorporate the state of the art in climate and crop prediction; and
- broaden the measures of forecast value to include development (e.g., poverty reduction, food security) and environmental benefits, and routinely include relative measures of value.

Acknowledgments. We thank Timothy Righetti for valuable comments and observations. This work has been supported in part by the International System for Analysis, Research and Training (START) Secretariat through its Visiting Scientist Program; and by the National Oceanic and Atmospheric Administration (NOAA) with Grant/Cooperative Agreement NA05OAR4311004. The views expressed in this paper are those of the authors and do not necessarily reflect the views of START, NOAA, or any of its subagencies.

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