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Chapter 7

MANAGING CLIMATE VARIABILITY IN AGRICULTURAL ANALYSIS

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ABSTRACT

This chapter offers some analytical insights for a comprehensive theoretical understanding of how to develop reliable ENSO-based crop yield forecasts and how to incorporate this information into an ENSO-sensitive farm-plan. A discussion on the usefulness of climate information for policy analysis is also presented. An improved basic understanding on the impact of seasonal climate variability (i.e., ENSO) on agriculture involves a more in-depth discussion of the value of the information as well as a broader knowledge of actual (or created) distinctions between adaptation, mitigation and response to climate risks. This chapter intends to inform the scientific community of the state-of-art on studies related to climate risk in agriculture and to help identify priorities for ongoing and future research.

INTRODUCTION

El Niño Southern Oscillation (ENSO) is a strong driver of seasonal climate variability that greatly impacts agriculture and regional economies (Legler et al., 1999). Advances in seasonal climate forecasting provide potential opportunities to reduce farm risk by tailoring

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agricultural management strategies to mitigate the impacts of adverse conditions or to take advantage of favorable conditions (Letson et al., 2001). Indeed, previous research has shown that improved ENSO forecasts could significantly impact the economic wellbeing of farmers in the Southeast U.S. by helping them not only to select an optimum farm-plan, but also by assisting them in the selection of the best crop insurance strategy and/or the most adequate federal aid program (Cabrera et al., 2007). Additionally, Cabrera et al. (2006a) have shown that seasonal climate information can be used to facilitate dairy farmers in complying with the new environmental regulations.

Economic benefits of seasonal climate forecast information have also been reported for semi-arid regions in developing countries (e.g., Roncoli, 2006). Traditional production practices in these less-favorable areas rely on rainfed technologies making them extremely sensitive to variations in rainfall. Thus, improvements in the dissemination of seasonal rainfall forecasts have been proposed as a reliable strategy to protect and boost household and national food security among environmentally and economically vulnerable regions (Dilley, 2000).

Managing climate risk is especially important in agriculture not only for the direct impact that climate has on production, but also for the tendency of most farmers to be risk averse. Risk aversion implies that farmers do not optimize their farm-plan for an upcoming season with average market and climate condition. Instead, they assume adverse conditions (Rosenzweig and Binswanger, 1993). Thus, reducing uncertainties of seasonal climate forecasts may help farmers select more profitable farm management strategies.

Nonetheless, climate information by itself is of little help to farmers and decision-makers unless it is presented in a way that it can be incorporated into managerial and policy processes. Cabrera et al. (2007) argue that farm decisions are also influenced by exogenous forces like fixed market windows, fluctuation in market prices of both inputs and outputs, and policies and regulations from local and federal governments that may enhance or limit the usefulness of the climate information. Furthermore, even in the event of a perfect forecast of an ENSO phase (i.e., El Niño, La Niña and Neutral), there is still great intra-phase climate variability and uncertainty that significantly impacts farm risk. In addition, due to the complexity of agricultural systems, non-rigorous statistical analysis may misinterpret or overweigh the impact of climate on agriculture.

To address these issues, alternative methodological frameworks have being developed in recent years to help farmers and policy-makers cope with climate uncertainty and other risks (e.g., Liu et al., in press; Cabrera et al., 2009; Rubas et al., 2006; Meza et al., 2003; Letson et al., 2001; Hammer et al., 2001; Mjelde and Hill, 1999). Also, further and faster advances expected in the sciences of climate and weather forecasting require the development of refined economic frameworks and analytical methods to help decision-makers take advantage and better assimilate this improved climatic information.

Consequently, the goal of this chapter is to offer the scientific community a systematic review of how to incorporate climate information when studying agricultural production and risk management. To do so, we first present some evidence of the impact of ENSO on agricultural production. Then, we present a comprehensive framework to use climate sensitive crop-yield models. Based on these models we propose a framework to account for climate risk in the development of optimum farm-plans. Next, we depict some thoughts on the usefulness of climatic information on policy making. Finally, we end this chapter by presenting some ideas for future research.

ENSO Impacts on Agriculture

Agriculture is a climate dependent activity, and because ENSO is one of the most important drivers of seasonal climatic variability around the world, it is expected that there would be correlations of different magnitudes and direction between crop yields and ENSO events. Furthermore, the capability of forecasting a specific ENSO phase has opened the opportunity of using this kind of information to predict with some level of skill future levels of agriculture production.

The impact of ENSO forecasts has been reported by several studies. For instance, Lagos and Buizer (1992) reported that a forecast of the mild El Niño in 1986/87, guided farmers on the coast of Peru (an area directly affected by El Niño) to plant cotton and rice in ratios resulting in higher yields compared with previous cropping seasons without forecasts. In the western South Pacific Ocean, Kuhnel (1994) reported the negative effect of El Niño on the production of sugarcane in Australia, whereas Meinke and Hammer (1997) reported positive effects on the production of peanut. In western South America, Podestá et al. (1999) reported increases (decreases) in maize and sorghum yield during El Niño (La Niña) in the Argentine Pampas (central-eastern Argentina), whereas Roel and Baethgen (2006) reported the opposite response of Uruguayan rice production. Hansen et al. (1999) reported ENSO impacts on winter vegetable production in Florida, Selvaraju (2003) assessed its effects on the production of grains in India, and Phillips and McIntyre (2000) analyzed its effects on several crops in parts of Uganda.

Framework for ENSO-Based Crop Yield Forecasting

Although there is strong evidence of the relation between ENSO and crop yields, empirical studies on this subject should follow a rigorous scientific framework in order to reduce the risk of finding inaccurate, artificial and misleading relationships between ENSO and crop yields. The following steps give a conceptual framework of how to perform a statistical analysis and the issues to take into consideration for the development of accurate ENSO-based crop yield forecasting.

Detrending Crop Yield Data

Examining the impact of Southern Oscillation on Texas sorghum and winter wheat yields, Mjelde and Keplinger (1998) found that technological changes tend to hide the effects of seasonal climate factors like ENSO. Many non–climatic factors influencing crop yield time series include: 1) changes in varieties; 2) soil quality, 3) technology (e.g., mechanization, shifts between rainfed and irrigated production); 4) and market influences on intensity of production and input use. Therefore, when a technological trend is apparent, it is necessary to remove it from the crop yield series before starting looking for correlations between crop productivity and climate. In areas with multi-decade unchanged traditional crop management, this procedure can obviously be overlooked.

To detrend the crop yield time series, it is assumed that climatic influences on crop yields generally occur at a higher frequency than non–climatic influences (Baigorria et al., 2008; Podestá et al., 1999). Therefore, a low-pass spectral filter (Press et al. 1989) can be used to obtain the annual yield residuals. This methodology first removes the linear trend. Then it is necessary to apply a Fourier transformation and remove low-frequency variations. Finally, the inverse Fourier transformation is applied and the linear trend is added again. The choice of the length of the low frequency period is arbitrary, so it is recommended to try periods larger than 10 years to avoid the removal of annual fluctuations in yield associated with climate variability. It is also important that detrending has to be done for a specific location because places, even those close one to another, could respond to a different low frequency period, and that the removed trend must be always go upward in time.

Statistical Comparisons

After detrending crop yields, the new crop yield residual time series must be divided according to each ENSO-phase. Timing is an important issue during the categorization (i.e., the cropping season) and must concur with or follow the ENSO event. This is especially important in the case of northern hemispheric lands where crops are planted from March to July (depending mostly on the latitude and the crop) whereas ENSO events develop during spring and summer in the southern hemisphere (winter in the northern hemisphere). Then, higher correlations between crop yields and ENSO events should be expected for summertime crops in the southern hemisphere (e.g., Lagos and Buizer, 1992; Podestá et al., 1999) and wintertime crops in the northern hemisphere (e.g., Hansen et al., 1999). However, summertime crops in the northern hemisphere can also be affected because changes in rainfall patterns during previous months can modify soil moisture conditions prior or during planting (e.g., Frassie et al., 2006). Apart from the well-known direct connection, there is also a lag time effect, from weeks to months, between the occurrence of an ENSO event in the Tropical South Pacific and more distant areas as the warm (cold) water moves. This could also modify regional climate patterns affecting spring and summer cropping seasons. In the case of multiyear crops like sugarcane, productivity levels must be related to ENSO events occurring up to a year before harvesting (Kuhnel, 1994).

After dividing the time series according to the three ENSO-phase categories, these datasets must be statistically compared in order to test the hypothesis of the influence of ENSO on crops yields. To perform this, an analysis of variance *F*-statistic (ANOVA) gives the result if at least one of the ENSO-based crop yield categories is statistically different from the others. If statistical significance is found, a multiple range test such as Duncan's multiple range test or Tukey's test can be applied in order to identify which ENSO-based crop yield category(ies) significantly differ from the others (Baigorria et al., 2007a; Hansen et al., 1999).

Use of Dynamic Crop Models

Whether or not a significant difference among the ENSO-based crop yield categories is found, previously calibrated and validated dynamic crop models can support looking for alternative crop management strategies for using categorical ENSO forecasts. Dynamic crop models are mathematical representations describing growth and development of a crop interacting with a soil profile (Wallach 2006) under a given sequence of atmospheric conditions.

Crop models have been calibrated and validated in different regions of the world (e.g. Fraisse et al., 2001; Jones et al., 2003; Lizaso et al., 2003) and used for studying impacts of climate variability and change in several regions around the globe (e.g., Adams et al., 2003; Baigorria et al., 2007b; Dubroský et al., 2000; Hansen and Indeje, 2004; Legler et al., 1999; Meinke and Hammer, 1997).

Furthermore, crop models have been used to find best management practices by changing crop management under different ENSO-phases (Cabrera, et al., 2006b; Paz, et al., 2007; Podestá et al., 2002; Steele, et al., 2001). Changing crop, crop cultivars, planting dates, nitrogen fertilization, among others, are farm-feasible alternatives. Since crop models can simulate crop responses to these alternative management options, they constitute an efficient tool to evaluate the different seasonal climate scenarios provided under different ENSO-phases.

Uncertainty

Lastly, although by definition, El Niño and La Niña events are well defined by establishing spatial (El Niño Regions), temporal (6 months) and thermal (± 0.5°C using 5-month running mean) thresholds in the Tropical South Pacific, intensity and volume of the total amount of warm (cold) oceanic water differ among events within each ENSO-phase. This internal variability within categories creates uncertainties in the interpretation of how an ENSO event affects crop yields in a given location.

The best way to introduce this uncertainty in the analysis is running the crop models using all the available years of meteorological information for each ENSO-phase and not only one representative year.

In this way, probability distributions of the expected yields under each ENSO-phase are obtained. One problem of this approach is the limited historical record of meteorological data and issues related to the errors and missing values. Weather generators are statistical tools that produce daily synthetic meteorological values that reproduce the main statistics of the historical record (e.g., Richardson and Wright, 1984; Schoof et al., 2005). The versatility of these weather generators opens the possibility to modify the analysis in order to be driven by specific climate events such as ENSO-phase (Grondonda et al., 2000) and climatic change (Dubroský et al., 2000).

By using these tools it is possible then to generate hundreds of realizations consistent with a specific ENSO phase, thus making it possible to generate probability distributions of expected values and its use as input for other applications such as those described in following sections of this chapter.

The following section focuses on the impact of climate risk on farm decision making. First we present the foundation of farm-risk analysis. Then we describe a framework for incorporating seasonal climate risk in an optimal farm-plan model.

AGRICULTURAL CLIMATE RISK DECISION MAKING

As we have portrayed, agricultural production is very sensitive to climate variability. In addition, agriculture is also affected by many other factors like rural policies, prices of inputs and outputs, international trade, etc. That is, an agricultural decision-making process is performed under risky conditions. Anderson et al. (1977) state that any risky decision may account for the following five components: 1) alternatives, 2) conditions, 3) probabilities, 4) consequences, and 5) value. These components can be defined for an agricultural scenario under seasonal climate variation as follows. *Alternatives* are all potential actions the decision maker can select to reduce risk (e.g., crop variety, planting date, irrigation schemes, etc.). The *Ambient* conditions include seasonal climate variability that affects agricultural production (e.g., wetter and colder summer conditions during El Niño, or drier and warmer winter conditions during La Niña in Florida). Prior *probabilities* are the chances of historical occurrences of each of the possible conditions (e.g., ENSO neutral years have a historical probability of once every two years). These probabilities are associated with their conditions under a set of selected alternatives leading to particular *consequences* in the outcomes. The consequences include the relative chances of all potential occurrences (e.g., better than usual yield due to increased precipitation during a predicted El Niño year will be offset by the alternative chances of not occurring in an El Niño year.). Finally, the *value* represents the measurable outcome (usually a monetary value) of the alternative selected under the risky conditions. For example, the net revenues of selecting a pest control management because of a seasonal climate forecast needs to be weighed against the decision of not using the climate information.

Dijkhuizen et al. (1997, p. 136) add that based on the complexities of the agricultural sector, five extra elements should be considered. These new elements adapted to climate risk decision making are: 1) opportunity of using the climate information; 2) defining actions to be taken with the climate information; 3) gathering, synthesizing and analyzing the information; 4) making and implementing the decision; and 5) evaluating the results of the decision of using or not the climate information.

To model the farm decision-making process under climate uncertainty researchers have been using four major alternative methodologies (Rubas et al., 2006): 1) decision theory, 2) equilibrium modeling, 3) game theory, and 4) mechanism design theory. From this group, decision theory has remarkably dominated the literature on climate forecast applications in agriculture. Decision theory assumes that a single decision agent (i.e., a farmer) makes a decision that will have consequences on the farmer’s enterprise. However this method does not account for the effect on other farms or surrounding enterprises. This assumption limits the decision theory approach to be farm-specific and cannot be used for large scale studies, in which case the other three methods would be more appropriate. Nonetheless, it is important to indicate that the other three alternative methods are highly theoretical frameworks, and consequently, less suitable for developing practical advice for farmers and decision makers. Consequently, the rest of this section focuses only on thoroughly describing the decision theory.

Decision theory implies the solution of an optimization problem that involves the utility function. Specifically, the model maximizes the expected utility subject to the expected returns based on a seasonal climate forecast obtained from prior knowledge.

Decisions in this context include the *risk preference* of the decision maker. Farmers, as do most people, tend to be risk averse decision makers. There have been several attempts to characterize farmers' preferences on risks. The most widely used model to characterize risk decision preference in agriculture using climate information has been the *expected utility function (EU).* The EU weighs the probability of each potential outcome generating a comparable index to help in the decision. In order to implement an EU model it is necessary to have the risk preferences of the farmers. The concept of *certainty equivalent (CE)* or, in other words, the willingness of a decision maker to trade a lower value, more secure enterprise for a higher value, less secure enterprise. The CE function has proven to be a useful technique to characterize farmers' risk preferences. Several studies on climate decisions have used Hardaker (2004) farmers' risk aversion typology to classify farmers as risk neutral, hardly averse, rather averse, very averse or almost paranoid.

A relatively new method adapted to agricultural climate decision making is the *conditional value at risk* (CVaR). The CVaR has been widely used in financial problems and introduced recently to agriculture (Cabrera et al., 2009; Liu et al., in press). Different from the utility function, the CVaR does not assign risk preferences to the decision makers *per se*. The CVaR, instead, finds the optimal frontier curve and characterizes risk proposals according different levels of risk of success or failure.

An additional concept of importance in agriculture decision making is the *Bayes' theorem* that goes one step further on the probabilities of outcomes when using climate information. Whereas an initial analysis of the historical outcomes will rely on historical chances of outcomes (e.g., El Niño occurs 25% of the years and during an El Niño year there will be 30% chance of above average precipitation) and consequently analyze only what these probabilistic outcomes would be, the Bayesian approach includes, in addition, the probability of the actual outcomes related to those predicted with the historical data. Consequently, under a Bayesian framework, there will be a distinction of 'prior' (historical) and 'posterior' (observed) probabilities. The Bayesian method has proven useful in several areas of agriculture (e.g., pest control and herd health) and has also been applied on climate use in agriculture (Stern and Easterline, 1999). By logical deduction, decision makers would make 'better' decisions if they knew how good the prediction has been in recent past years.

However, we argue that the Bayesian approach is not the best choice under ENSO based seasonal climate prediction use for agricultural production due to the following reasons: 1) even for a perfect ENSO forecast, variability inside the phase will make trivial the use of posterior probabilities; 2) information to characterize ENSO phases is limited in nature (i.e., less than 20 El Niño occurrences have been documented to date) and new information is more valuable to complete historical distributions than to create new distributions; and 3) the introduction of Bayesian factor into the analyses introduces another source of variability that is difficult to account for by the decision-maker. Many of the latest studies on climate agriculture decision-making have better used Monte Carlo techniques to account for missing information in the distribution of ENSO phases (Cabrera et al., 2007; Letson et al., 2005).

Although different scientific articles have used the methodologies presented above to control for climate variability on agricultural studies, a thorough analysis of the impact of climate on agriculture requires the implementation of a formal framework. In the following section we describe a framework to introduce climate information in farm optimization analyses.

Introducing Seasonal Climate Information in Farm Optimization Analyses

The introduction of seasonal climate information when analyzing farm risk must follow a rigorous framework to avoid biased results. Based on the literature and on our experience we propose the following framework to incorporate seasonal climate information when studying the farm decision-making process. This framework is composed of the following steps: 1) Identify the problem and the opportunity of using ENSO-based climate information: 2) Gather adequate data; 3) Synthesize, organize, analyze, and expand the data; 4) Set up the optimization model and the risk preferences; and 5) Assess the value of climate information in agricultural production.

Identify the Problem and the Opportunity of Using Seasonal Climate Information

Agriculture is a climate vulnerable enterprise and there are easily identifiable potential opportunities to use seasonal ENSO-based climate information to improve agricultural production. Some examples are land allocation, variety and crop selection, and planting dates. For instance, rainfall in Florida is highly sensitive to ENSO phases with an average excess of about 40% of the normal rainfall during an El Niño year and with deficits of about 30% during a La Niña year (Jagtap et al., 2002). Thus, most of the crops raised in Florida are influenced by ENSO conditions (Hansen et al., 1999). An analysis of 40 years of crop yield historical data (information available at AgroClimate.org) indicates that peanut would have higher than average yields during both La Niña and El Niño years (4.4 and 3.3% above average, respectively). Conversely, cotton yields would be lowered by 9.1% and 0.3% during La Niña and El Niño years, respectively. And, for corn there would be an increase of yields during La Niña years of 0.7% and a decrease of 17% during El Niño years.

A closer look at this information suggests that farmers potentially have many alternatives to adapt to climate variability and to avoid the economic consequences of an abnormal climate year. However, current research offers limited information on the impact of ENSO on production. Thus, further analyses of the impact of ENSO on all available crops in a specific area are much needed to offer farmers the necessary tools to establish sustainable long-run farm-plans.

Gather the Adequate Data

To perform an accurate study, different sources of information will be needed. It is critical to obtain reliable and long time series of daily weather data which contain all the necessary parameters for the agricultural enterprises to be studied. For instance, Cabrera et al. (2007) used data on maximum and minimum temperatures, incoming solar radiation, and precipitation on a daily basis for a 65-year period. These parameters were selected because they were needed to simulate process-based crop growth and crop yields. On the other hand, if animal production were the primary objective in the analysis, relative humidity would be essential to characterize thermal heat stress.

Another important set of data is the agronomic information. This information is needed to find all alternatives management options for a specific crop. For example, in North Florida, the variety Georgia Green of peanut is planted between mid-April and mid-June, with a traditional N fertilization of 10 kg/ha at planting. This information will be used to simulate the growth and yield of this enterprise and compare it with other alternative management options. Crop rotation and land allocation are also important data to constrain the optimization model in the most realistic way.

Economic information such as cost of production and commodity prices are also crucial. Although cost of production (including fixed and variables costs) can be accepted as constant throughout the analysis, commodity prices need to be introduced as probabilistic distributions. In the risk decision making scheme, profitability is crucial. When considering constant costs of production, total revenue becomes the most important factor in decision-making and this is calculated by multiplying the yields of the agricultural enterprises by their market prices (both factors highly variable and uncertain). Therefore, a reliable source of historical commodity prices that allow a fair characterization of the price distributions is needed.

Synthesize, Organize, Analyze, and Expand the Data

Once the different sources of information are available and before engaging in further analyses, a quality control is required. Plotting and performing descriptive statistics would help in finding inconsistencies, missing information, and outliers that need to be examined. For the weather information it is important to perform these analyses disaggregating the data by ENSO phases.

A thorough assessment of climate risk and forecast value needs a more complete picture of the distribution of ENSO past events. For instance, during the last 64 years there have been only 14 El Niño events and 16 La Niña events. To obtain more robust results Letson (2005) expanded the historical weather data using stochastic weather generators to produce synthetic daily weather series with statistical resemblance to original historical data. Another solution is to use the available historical weather data to simulate agricultural yields and then simulate series of yields characterized by ENSO phases as was performed in Cabrera et al. (2007).

A similar dilemma is faced for commodity prices. Only a limited number of years of price data would be available and to give a fair analysis of each ENSO phase a similar matching price is needed. In Cabrera et al. (2007, 2009) and Letson et al. (2005), a distribution of 990 records of crop yields were generated for each ENSO phase, consequently a distribution of 990 price-years were generated for each commodity. Commodity prices were assumed to be completely independent of ENSO climate characteristics. Agricultural commodity prices could have large distortions because of farm government programs and other non-farm controllable situations, which need to be considered during the generation of these price series. Lastly, different policies can be set with the model to analyze impacts of external forces in price distortion.

Set Up the Optimization Model

The goal of this subsection is not to give the reader a mathematical derivation of a farm optimization model under climate risk[1], but rather to walk the reader through the logical process of solving and understanding the decision problem. The objective of an optimization model is to find the maximum expected utility under a specific climatic condition, such as specific ENSO phase.

Technically speaking, the optimization model compares expected utilities of all possible sets of management strategies within the model restrictions. By iteration, the model keeps the strategies generating the higher net returns and discards the ones with lower returns. At the end, the model presents the set of management options that provides the highest farm expected utility. The model can be adapted in such a way that a farmer can select the best management option that accommodates a specific climate scenario.

A refinement of this analysis includes the incorporation of the level of risk aversion of the decision maker in the optimization process. This procedure can be performed by introducing a power function into the model. In doing so, the first step of the optimization will present a set of management practices that yields the maximum expected utility by risk aversion level. Next, the expected utility of all records need to be re-assembled using the optimal management.

Assess the Value of Climate Information on Agricultural Production

The value of climate information can be finally calculated as the difference between the expected utility of a model accounting for ENSO-based forecast minus the expected utility of a model solved not using ENSO sensitive data. Positive values for ENSO information have been reported by Cabrera et al. (2007, 2009), Letson et al. (2005) and Messina et al. (1999), among others. However, under risky conditions of climate and prices, there is a likelihood of having negative values for climate information as well. A negative value of the information means that the farm would have been better off without using climate information, which is a possibility that the farmer needs to evaluate for final decision.

The framework presented in this section allows farmers to make a more informed decision by including seasonal climate and other risks into their analysis. Depending on the decision-maker risk preference, it is possible to reduce or even eliminate the likelihood of negative values for climate information by trading it off with overall expected utility reduction.

It is important to highlight that a positive (negative) value for ENSO information does not mean that the farm will generate positive (negative) net returns, but rather that farmers will be better off (worst off) using seasonal climate information in their farm decision-making process.

[1] A good presentation of a farm-optimization model accounting for climate variability can be found in Letson et al. (2005).

POLICY, DECISION MAKING AND USEFULNESS OF CLIMATE INFORMATION

Our previous sections have shown that climate information can be highly valuable for both farmers and policy-makers. However, several issues may still prevent its complete applicability to develop policies and to help farmers in their decision-making process. One of the most important factors affecting the implementation of seasonal climate sensitive farm and economic models relates to the uncertainly of accurate prediction of weather forecasts. Quiggin and Horowitz (2003) argue that since the predictability of long-run climate systems are highly uncertain; farmers will take suboptimal economic decisions based on *ex post* response to climate information. For instance, farmers facing a run of dry seasons must choose whether or not to continue in business without knowing if the climate has undergone a permanent change or if the run of dry seasons is just a temporal random fluctuation.

In addition, routine availability of ENSO-based climate forecasts will not, by itself, increase agricultural incomes or lower production costs in ENSO-influenced regions. Climate information is but one of three parallel processes that comprise the forecasting process. In addition to the prediction itself, a communication process shares the prediction and a choice process focuses on decisions (Pielke, 1998, Pielke, et al. 2000). The research community's definition of a 'good' forecast does not necessarily agree with policy makers' or society's view of what is most important (Offutt, 1993). Partly the problem is one of communication. Fischhoff (1994) identifies several problems in communicating forecasts, including ambiguity regarding the event being predicted and what is being said about it, and the relevance of the forecast for users' problems. In their review of forecasts for the 1997/98 El Niño, Barnston et al. (1999) cite ambiguous descriptions of magnitude, time of onset, and duration. Also, different stakeholders have different preferences about what a forecast should do. Thus efforts to 'educate' the public are unlikely to make them see forecasts as experts do (Freudenburg and Rursch, 1994). It is important to mention that in recent years major efforts have been undertaken to develop agricultural decision support tools with the aim of helping farmers cope under climate uncertainties (Breuer et al., 2008). A good example is the AgroClimate web site (http://AgroClimate.org/) developed by the Southeast Climate Consortium. However, this is clearly an area that merits further research.

Another set of concerns for decision makers involves the application of seasonal climate forecasts. The mere existence of a technical innovation such as improved seasonal climate forecasts does not ensure that the innovation is refined or adaptable enough to meet potential users' needs (Schultz, 1964); and thus, forecast use has advanced slowly (Trenberth, 1997; Changnon, 1999; Goddard et al., 2001). Whether a climate forecast can be useful depends on four conditions: 1) the availability of a forecast of seasonal climate conditions relevant to decisions, with appropriate lead time, and geographic and temporal resolution; 2) the feasibility of alternative actions that can be taken in response to a climate forecast; 3) the ability to evaluate the outcomes of those alternative actions; and 4) the willingness of decision makers to adopt climate adaptive management in an already complicated decision-making environment.

Economists attempt to combine many of the concerns about forecast skill and application when they assume decision makers will use forecasts that are valuable. Forecast 'value' is based on the expected outcome from an improved, forecast-assisted decision compared to the expected outcome of the decision without the forecast. The value seasonal climate forecasts may have and under what decision circumstances (such as crops grown, resource conditions, and production technology) have become important public policy concerns. In many countries seasonal climate data, forecasts and technical assistance are often provided and subsidized by the public sector (Glantz, 2000). Estimating forecast value can help show if improved forecast provision and dissemination would offer more to society than other innovations, such as new or genetically modified seed varieties. Many have estimated how much value forecasts may have for agriculture (Mjelde et al., 1996; Hammer et al., 2001; Meza et al., 2003). Mjelde et al. (1998) and R. Katz's internet site (www.esig.ucar.edu/HP rick/agriculture.html) offer literature surveys of studies that estimate forecast value for agriculture.

While the notion of a potential value for seasonal climate forecasts has been established, questions of when they may be most valuable have proven harder to be resolved, in part because of the intricacy of many decision contexts. Seasonal climate forecast value perhaps most clearly depends on how good the forecast tends to be. Foremost in forecast value discussions has been its relationship to forecast quality measures, particularly skill (Katz and Murphy, 1997). Much important research has sought to link forecast skill and value (Murphy, 1997; Wilks, 1997). Once established for a given decision environment, the skill–value linkage allows researchers and users to evaluate the incremental benefits from actual or hypothetical forecast improvements.

The close association between forecast skill and value has led to some confusion, as noted by Murphy (1993). While forecast value depends partly on skill, the two concepts differ in important ways as Hartmann et al. (2002), and Meinke and Stone (2005) clarify: a highly skillful forecast could have no value, and one of modest skill, if well applied, could have value under the right circumstances. As Pielke et al. (2000, p. 366) note, "comparing a prediction with actual events does not provide sufficient information to evaluate its performance." Other influences on forecast value warrant attention, especially those that are random and region or application-specific (Wilks, 1997; Hartmann et al., 2002).

CONCLUSION

The goal of this chapter was to offer some analytical insights for a comprehensive theoretical understanding of how to produce an ENSO-based crop yield forecast and how to incorporate this information into a farm plan. A discussion on the usefulness on this kind of information for policy analysis was also presented. An improved basic understanding on the impact of seasonal climate variability (i.e., ENSO) on agriculture involves a more in-depth discussion of the value of the information as well as a broader knowledge of actual (or created) distinctions between adaptation, mitigation and response to climate risks. This chapter summarizes the available literature as well as our experience in this field and provides a starting point for further discussion.

Current research has shown that farmers can be better off by using seasonal climate information when deciding their farm plans. In addition, society would also gain if policy-makers adopt this knowledge when discussing rural policies, subsidies and aid programs. Nevertheless, agricultural technology is highly 'location specific' and must be adapted to the cultural and resource conditions where it is to be applied (Schultz, 1964). Although high quality research has been published on the impact of seasonal climate variability on agricultural production, the literature has focused on a handful of crops and in very limited geographic areas. Thus, much research is needed to expand our knowledge in this field.

On the other hand, farmers and decision makers may elect not to use seasonal climate forecasts for many reasons. One concern may be forecast quality, or the degree to which the forecast corresponds to subsequent observations. To be useful, a forecast must offer skill, or higher quality than that of a naïve forecasting system, such as the average conditions over many years for that location and time of year (i.e., climatology). Current understanding of sea surface temperature variability in the equatorial Pacific and its climatic impacts enables skillful forecasts of future sea surface temperature anomalies, although with errors (Landsea and Knaff, 2000).

Lastly, the literature on agricultural climate risk management is highly dominated by studies on crops. A reason for this situation may be that livestock spend part or all of their time in confinement, not having direct impact of the weather inclemency. However, we believe there are opportunities to expand and apply this area of research to livestock agriculture. Dairy cattle milk production alone, for example, is diminished between 68 and 2072 kg/cow per year in the US due to heat stress (St-Pierre et al., 2003), a condition that could be improved if ENSO-based information would be used to prepare actions on dairy farms.

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