MANAGING CLIMATE RISKS TO AGRICULTURE: EVIDENCE FROM EL NIÑO

Víctor E. Cabrera[1], Daniel Solís[2]*, Guillermo A. Baigorria[3], and David Letson[2]

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 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 USA by helping them to select an optimum farm plan and by assisting them in the selection of the best crop insurance strategy and the most appropriate federal aid program (Cabrera et al., 2007). Additionally, Cabrera et al. (2006a) have shown that seasonal climate information can be used to help dairy farmers develop management strategies that comply with 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 agricultural production practices in these less-favorable areas rely on rainfed technologies making them extremely sensitive to variation 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 because most farmers tend to be risk averse. Risk aversion implies that farmers do not optimize their farm-plan for an upcoming season with average market and climate conditions; instead, they manage for 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 such as fixed market windows, fluctuation in market prices of 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, or 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,

[1] Dept. of Dairy Science, University of Wisconsin, Madison, WI
[2] Rosenstiel School of Marine and Atmospheric Sciences, University of Miami, Tallahassee, FL
[3] Dept. of Agricultural and Biological Engineering, University of Florida, Gainesville, FL
[4] Rosenstiel School of Marine and Atmospheric Sciences, University of Miami, Miami, FL
* Corresponding author e-mail: d.solis@miami.edu

non-rigorous statistical analysis may misinterpret or overweigh the impact of climate on agriculture.

To address these issues, alternative methodological frameworks have been 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., 2007; 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 paper 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 paper by presenting some ideas for future research.

ENSO IMPACTS ON AGRICULTURE

Agriculture depends on climate dependent 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 information to predict agriculture production with some level of skill.

The impact of ENSO forecasts has been reported by several studies. 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 a negative effect of El Niño on sugarcane production in Australia, whereas Meinke and Hammer (1997) reported positive effects on peanut production. In western South America, Podestá et al. (1999) reported increases in maize and sorghum yield during El Niño and yield reductions during 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 a relation between ENSO and crop yields, empirical studies on this subject must follow a rigorous scientific framework in order to reduce the risk of finding inaccurate, artificial, or 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.

De-trending 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 confound the effects of seasonal climate factors, such as ENSO. Many non–climatic factors influence crop yield time series, including: 1) changes in varieties; 2) soil quality, 3) technology (e.g., mechanization, shifts between rainfed and irrigated production); 4) and market influences. 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. Only in areas with unchanged traditional crop management over multiple decades can this procedure be omitted.

To de-trend 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 smoothing 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 smoothing 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. De-trending has to be done for each location because even places close one to another could respond to a different smoothing 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 ENSO-phase. Timing of the crop season is an important issue during the categorization; the crop season must occur during or following an ENSO event. Timing is especially important in the case of northern hemisphere 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). Thus, 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 correlation, 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 time lag could modify regional climate patterns affecting spring and summer cropping seasons. In the case of multiyear crops such as sugarcane, productivity levels must be related to ENSO events occurring up to a year before harvest (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 categories significantly differ from the others (Baigorria et al., 2007a; Hansen et al., 1999).

Use of dynamic crop models

Whether or not a significant difference are found among the ENSO-based crop yield categories, previously calibrated and validated dynamic crop models can support efforts to identify 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 testing different crop management practices under different ENSO-phases (Cabrera, et al., 2006b; Paz, et al., 2007; Podestá et al., 2002; Steele, et al., 2001). Changing crops, crop cultivars, planting dates, and nitrogen fertilizer ammount, among others, are farm-feasible alternatives for responding to an ENSO-phase change. Because crop models can simulate crop responses to alternative management options, they constitute an efficient tool to evaluate the different seasonal climate scenarios provided under different ENSO-phases.

Uncertainty

Although El Niño and La Niña events are well defined by 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 oceanic water that is involved in the temperature anomaly 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 to simulate crop production using all the available years of meteorological information for each ENSO-phase and not only one representative year. In this way, probability distributions of 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 that can be used as inputs for other applications, such as those described in following sections of this paper. 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

Not only is agricultural production very sensitive to climate variability, it is also affected by many other factors, such as rural policies, prices of inputs and outputs, and international trade. That is, an agricultural decision-making process is performed under risky conditions. Anderson et al. (1977) state that any risky decision may be examined for the following five components: 1) alternatives, 2) conditions, 3) probabilities, 4) consequences, and 5) value. For an agricultural scenario under seasonal climate variation, a**lternatives** are all potential actions the decision maker can select to reduce risk (e.g., crop variety, planting date, irrigation schemes, etc.). **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 as 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 used four major alternative methodologies (Rubas et al., 2006): 1) decision theory, 2) equilibrium modeling, 3) game theory, and 4) mechanism design theory. Among this group, decision theory has 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. The rest of this section focuses only on decision theory.

Decision theory implies the solution of an optimization problem that involves a 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 useful 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 to assess financial risks and was introduced recently to agriculture (Liu et al., in press). Different from the utility function, CVaR does not assign risk preferences to the decision makers *per se*. Instead, CVaR 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's 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 for ENSO based seasonal climate prediction as applied to agricultural production for the following reasons: 1) even with a perfect ENSO forecast, variability inside the phase will make trivial the use of posterior probabilities; 2) information to characterize ENSO phases is limited, there have been fewer than 20 El Niño occurrences documented to date so new information is more valuable to complete historical distributions than to create new distributions; and 3) introduction of a Bayesian factor into the analyses introduces another source of uncertainty that is difficult to account for by the decision-maker. Many recent studies on agriculture decision-making in response to climate information 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.

SEASONAL CLIMATE INFORMATION FOR FARM OPTIMIZATION

The introduction of seasonal climate information when analyzing farm risks 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 (http://AgroClimate.org) indicates that on average peanut would yield more than the overall average during both La Niña and El Niño years (4.4 and 3.3% above average, respectively). Conversely, cotton would yield 9.1% less La Niña. Corn yields decrease 17% below average during El Niño years.

A closer look at this information suggests that farmers potentially have a 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 analysis of the impact of ENSO on all available crops in a specific area is much needed to offer farmers the necessary tools to establish sustainable long-run farm-plans.

Gather 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 daily data of maximum and minimum temperatures, incoming solar radiation, and precipitation for a 65-year period. These parameters were selected because they were needed to simulate process-based crop growth and crop yields. If animal production were the primary objective of 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 alternative 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 would 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 of which are 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 data

Once the different sources of information are available and before engaging in further analyses, quality control is required. Plotting and performing descriptive statistics help to find inconsistencies, missing information, and outliers that need to be examined. For 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. To give a fair analysis of each ENSO phase a similar matching price is needed, but there are price data available. Cabrera et al. (2007) and Letson et al. (2005) generated a distribution of 990 records of crop yields 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.

Construct optimization model

The goal of this subsection is not to give the reader a mathematical derivation of a farm optimization model under climate risk, which may be found in Letson et al. (2005). Rather we will present 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 climate condition, such as a 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 that generate higher net returns and discards strategies with lower returns. In the end, the model presents the set of management options that provides the highest farm expected utility. The model can be modified so 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 for agricultural production

The value of climate information can be 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), 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 not using climate information, which is a possibility that the farmer needs to evaluate before making a 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’s 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 or negative value for ENSO information does not mean that the farm will generate positive or negative net returns, but rather that farmers will be better or worse off using seasonal climate information in their farm decision-making process.

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 factors may prevent its application to the development of 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 predictions 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 temporary 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 disseminates the prediction and a choice process reaches a decision (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). The problem is partly 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 with climate uncertainties (Breuer et al., 2008). 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 that is 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 with the expected outcome of the decision without the forecast. The potential value of seasonal climate forecasts and their application within a decision environment, 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 provided and subsidized by the public sector (Glantz, 2000). Estimating forecast value can help show whether improved forecast provision and dissemination would offer more to society than other innovations, such as new or genetically modified seed varieties. Many economists have estimated the potential value that 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 resolve, in part, because of the intricacy of many decision contexts. Seasonal climate forecast value perhaps most clearly depends on the accuracy of the forecast. 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 considerable 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

An improved basic understanding of 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. 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.

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, with relatively little emphasis on other parts of the agricultural system. 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.

REFERENCES

Baigorria, G.A., Hansen, J.W., Ward, N., Jones, J.W., & O'Brien, J.J. (2008) Assessing predictability of cotton yields in the southeastern United States based on regional atmospheric circulation and surface temperatures. Journal of Applied Meteorology and Climatology, 47, 76–91.

Baigorria, G.A. (2007). Assessing the use of seasonal climate forecasts to support farmers in the Andean Highlands. In: Sivakumar, M.V.K. & Hansen, J. (Eds.), Climate prediction and Agriculture: Advances and challenges. (pp. 99–110). Springer, Berlin/Heidelberg.

Baigorria, G.A., Jones, J.W., & O'Brien, J.J. (2007a). Understanding rainfall spatial variability in the southeast USA. International Journal of Climatology, 27, 749–760.

Baigorria, G.A., Jones, J.W., Shin, D.W., Mishra, A., & O'Brien, J.J. (2007b). Assessing uncertainties in crop model simulations using daily bias-corrected Regional Circulation Model outputs. Climate Research, 34, 211–222.

Barnston, A., Glantz, M.H., & He Y. (1999). Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Niño episodes and the 1998 La Niña onset. Bulletin of the American Meteorological Society 80, 217–243.

Breuer, N.E., V.E. Cabrera, K.T. Ingram, K. Broad, and P.E. Hildebrand. (2008). AgClimate: A case study in participatory decision support system development. Climatic Change 87, 385–403.

Cabrera, V.E., Breuer, N.E., Hildebrand, P.E. (in press). Participatory modeling using climate forecasts. Climatic Change.

Cabrera, V. E.**,** Letson D., & Podestá G. (2007). The value of the climate information when farm programs matter. Agricultural Systems, 93, 25–42.

Cabrera, V. E., Hildebrand, P.E. Jones, J.W., Letson, D., & de Vries, A. (2006a). An integrated North Florida dairy farm model to reduce environmental impacts under seasonal climate variability. Agriculture, Ecosystems and Environment, 113, 82–97.

Cabrera, V.E., Fraisse, C., Letson, D., Podesta, G., & Novak, J. (2006b). Impact of climate information in reducing farm risk by selecting crop insurance programs. Transactions of the ASABE, 49, 1223–1233.

Changnon, S.A. (1999). Rapidly expanding uses of climate data and information in agriculture and water resources. Bulletin of the American Meteorological Society, 80, 821–830.

Dijkhuizen A.A., Morris, R.S. (eds) (1997). Animal health economics, principles and applications. Post Graduate Foundation in Veterinary Science, University of Sydney. P. 136.

Dilley, M. (2000). Reducing vulnerability to climate variability in Southern Africa: the growing role of climate information. Climatic Change, 45, 63–73.

Dubrovský, M., Zalud, Z., & Stastna, M. (2000). Sensitivity of CERES-maize yields to statistical structure of daily weather series. Climate Change, 46, 447-472

Fischhoff, B. (1994). What forecasts (seem to) mean. International Journal of Forecasting, 10, 387–403.

Fraisse, C.W., Sudduth, K.A., & Kitchen, N.R. (2001). Calibration of the CERES-Maize model for simulating site-specific crop development and yield on Claypan soils. Applied Engineering Agriculture, 17, 547–556.

Fraisse, C.W., Breuer, N.E., Zierden, D., Bellow, J.G., Paz, J., Cabrera, V.E., Garcia y Garcia, A., Ingram, K.T., Hatch, U., Hoogenboom, G., Jones, J.W., & O'Brien, J.J. (2006) AgClimate: A climate forecast information system for agricultural risk management in the southeastern USA. Computers and Electronics in Agriculture, 53, 13–27.

Freudenburg. W., & Rursch, J. (1994). The risks of putting the numbers in context. Risk Analysis, 14, 949-58.

Glantz, M.H. (2000). Currents of change: El Niño's impact on climate and society (Second edition). Cambridge University Press.

Goddard, L., Mason, S.J., Zebiak, S.E., Ropelewski, C.F., Basher, R., & Cane M.A. (2001). Current approaches to seasonal-to-interannual climate predictions. International Journal of Climatology, 21, 1111–52.

Grondona, M.O., Podestá, G.P., Bidegain, M., Marino, M., & Hordij, H. (2000). A stochastic precipitation generator conditioned on ENSO phase: a case study in southeastern South America. Journal of Climate, 13, 2973–2986.

Hammer, G.L., Hansen, J.W., Phillips, J.G., Mjelde, J.W., Hill, H.S.J., Love, H.A., & Potgieter, A.B. (2001). Advances in application of climate prediction in agriculture. Agricultural Systems, 70, 515–553.

Hansen, J.W., & Indeje, M. (2004). Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. Agricultural and Forest Meteorology, 125, 143–157.

Hansen, J.W., Jones, J.W., Kiker, C.F., Hodges, A.H., 1999. El Niño Southern Oscillation impacts on winter vegetable production in Florida. Journal of Climate, 12, 92–102.

Hartmann, H.C., Pagano, T.C., Sorooshian, S., & Bales, R. (2002). Confidence builders: Evaluating seasonal climate forecasts from user perspectives. Bulletin of the American Meteorological Society, 83, 683–98.

Jagtap, S.S., Jones, J.W., Hildebrand, P., Letson, D., O'Brien, J.J., Podestá, G., Zierden, D., & Zazueta, F. (2002). Responding to stakeholder's demands for climate information: from research to applications in Florida. Agr. Sys. 74, 415–430.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K,J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., & Ritchie, J.T. (2003). The DSSAT cropping system model. European Journal of Agronomy, 18, 235–265.

Khunel, I. (1994) Relationship between the Southern Oscillation Index and Australian sugarcane yields. Australian Journal of Agricultural Research, 45, 1557–1568.

Lagos, P., & Buizer, J. (1992) El Niño and Peru: A nation's response to interannual climate variability. In: Majumdar, S.K., Forbes, G.S., Miller, E.W. & Schmalz, R.F. (Eds). Natural and technical disasters: causes, effects and preventive measures. (pp. 223–228). The Pennsylvania Academy of Science.

Landsea, C.W., & Knaff, J.A. (2000). How much skill was there in forecasting the very strong 1997–1998 El Niño? Bulletin of the American Meteorological Society, 81, 2107–2119.

Legler, D. M., Bryant, K.J., & O'brien J.J. (1999). Impact of ENSO-related climate anomalies on crop yields in the U.S. Climatic Change, 42, 351–375.

Letson, D., Podestá, G. P., Messina, C. D., & Ferreyra, A. (2005). The uncertain value of perfect ENSO phase forecasts: stochastic agricultural prices and intra-phase climatic variations. Climatic Change, 69, 163–196.

Letson, D., Llovet, I., Podestá, G., Royce, F., Brescia V., Lema, D., & Parellada, G. (2001). User perspectives of climate forecasts: crop producers in Pergamino, Argentina. Climate Research, 19: 57–67, 2001

Liu, J., Chunhua, M., Cabrera, V.E., Uryasev, S., & Fraisse, C.W. (in press). Optimizing crop insurance under climate variability. Journal of Applied Meteorology and Climatology.

Lizaso, J.I., Batchelor, W.D., Westgate, M.E., & Echarte, L. (2003). Enhancing the ability of CERES-Maize to compute light capture. Agricultural Systems, 76, 293–311.

Meinke, H., & Hammer, G.L. (1997). Forecasting reagional crop production using SOI phases: an exmple for the Australian peanut industry. Australian Journal of Agricultural Research, 48, 789–793.

Meinke, H., & Stone, R.C. (2005). Seasonal and interannual climate forecasting: New tool for increasing preparedness to climate variability and change in agricultural planning and operations. Climatic Change, 70, 221–253

Meza, F.J., Wilks, D.S., Riha, S.J., & Stedinger, J.R. (2003). Value of perfect forecasts of sea surface temperature anomalies for selected rain-fed agricultural locations of Chile. Agriculture Forest and Meteorology, 116, 117–135.

Mjelde, J.W., & Hill, H.S.J. (1999). The effect of improved climate forecasts on variable costs, input usage, and production. Agricultural Systems, 60, 213–225.

Mjelde, J.W., Hill, H.S.J., & Griffiths, J.F. (1998). Review of current evidence on climate forecasts and their economic effects in agriculture. American Journal of Agricultural Economics, 80, 1089–1095.

Mjelde, J.W., & Keplinger, K. (1998). Using the southern oscillation to forecast Texas winter wheat and sorghum crop yields. Journal of Climate 11, 65–70.

Mjelde, J.W., Thompson, T.N., & Nixon, C.J. (1996). Government institutional effects on the value of seasonal climate forecasts. American Journal of Agricultural Economics, 78, 175–188.

Murphy, A. H. (1997). Forecast verification. In: Katz, R., & Murphy, A.H. (Eds.), Economic value of weather and climate forecasts (pp. 19–74). Cambridge University Press.

Murphy, A.H. (1993). What is a good forecast? An essay on the nature of goodness in weather forecasting. Weather Forecast, 8, 281–293.

Offutt, S. (1993). Bridging the gap between policymakers and academics. In: Kaiser, H. M., & Drennen, T. E. (Eds.), Agricultural dimensions of global change (pp. 280-286). St. Lucie, FL: St. Lucie Press,

Paz, J.O., Fraisse, C.W., Hatch, L.U., Garcia y Garcia, A., Guerra, L.C., Uryasev, O., Bellow, J.G., Jones, J.W., & Hoogenboom, G. (2007). Development of an ENSO – based irrigation decision support tool for peanut production in the southeastern US. Computers and Electronics in Agriculture, 55, 28–35.

Phillips, J., & McIntyre, B. (2000). ENSO and interannual rainfall variability in Uganda: Implications for agricultural management. International Journal of Climatology, 20, 171–182.

Pielke, R.A. (1998). What is a good forecast? WeatherZine, NCAR monthly electronic newsletter, Issue No. 8. Available From: www.esig.ucar.edu/socasp/zine/

Pielke, R.A., Sarewitz, D., & Byerly, R. (2000) Decision making and the future of nature. In: Pielke R. A., Sarewitz, D., & Byerly, R. (Eds.), Prediction: science, decision making and the future of nature (pp. 361–387). Covelo, CA: Island Press.

Podestá, G.P., Messina, C.D., Grondona, M.O., & Magrin, G.O. (1999) Associations between grain crop yields in central-eastern Argentina and El Niño-Southern Oscillation. Journal of Applied Meteorology, 38, 1488–1498.

Podestá, G.P., Letson, D., Messina, C., Royce, F., Ferreyra, R.A., Jones, J.W., Hansen, J., Llovet, I., & Grondona, M. (2002) Use of ENSO-related climate information in agricultural decision making in Argentina: a pilot experience. Agricultural Systems, 74, 371–392.

Richardson, C.W., Wright, D.A. (1984). WGEN: a model for generating daily weather variables. U.S. Department of Agriculture, Agricultural Research Service, Washington, D.C.

Roel, A., & Baethgen, W.E. (2007). Towards the development of a spatial decision support system (SDSS) for the application of climate forecasts in Uruguayan rice production sector. In: Sivakumar, M.V.K. & Hansen, J. (Eds.), Climate prediction and Agriculture: Advances and challenges. (pp. 89–97). Springer, Berlin/Heidelberg.

Roncoli, C. (2006). Ethnographic and participatory approaches to research on farmers’ responses to climate predictions. Climate Research, 33, 81–99.

Rosenzweig, M.R., & Binswanger, H.P. (1993). Wealth, weather risk and the composition and profitability of agricultural investments. The Economic Journal, 103**,** 56–78.

St-Pierre, N.R., Cobaniv, B., & Schnitkey, G. Economic losses from heat stress by US livestock industries. J. Dairy Sci. 86(E. Suppl.):E52-E77.

Rubas, D.J., Hill, H.S.J. & Mjelde, J.W. (2006). Economics and climate applications: exploring the frontier. Climate Research, 33, 43–54.

Schultz, T.W. (1964). Transforming traditional agriculture. New Haven, CT: Yale University Press.

Schoof, J.T., Arguez, A., Brolley, J., & O'Brien, J.J. (2005). A new weather generator based on spectral properties of surface air temperatures. Agricultural and Forest Meteorology, 135, 241–251.

Selvaraju, R. (2003) Impact of El Niño–Southern Oscillation on Indian foodgrain production. International Journal of Climatology, 23, 187–206.

Steele, D.D., Stegman, E.C., & Knighton, R.E. (2000). Irrigation management for corn in the northern Great Plains, USA. Irrigation Science, 19, 107–114.

Stern, P.C., Easterling, W.E. (1999). Making climate forecasts matter. National Research Council, Panel on Human Dimensions of Seasonal-to-Interannual Climate Variability, National Academy Press, Washington, DC

Trenberth, K.E. (1997). Short-term climate variations: Recent accomplishments and issues for future progress. Bulletin of the American Meteorological Society, 78, 1081–1096.

Wallach, D. (2006). The two forms of crop models. In: Wallach, D., Makowski, D., & Jones, J.W. (Eds.), Working with dynamic crop models: Evaluation, analysis, parameterization, and application (pp. 3–9). Elsevier, Amsterdam, the Netherlands.

Wilks, D.S. (1997). Forecast value: prescriptive decision studies. In: Katz, R.W. & Murphy A.H. (Eds.), Economic value of weather and climate forecasts (pp. 109–145). Cambridge University Press.