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Agriculture, Ecosystems and Environment 82 (2000) 169–184

Agriculture Ecosystems & Environment

www.elsevier.com/locate/agee

Potential benefits of climate forecasting to agriculture

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Abstract

Climate variability leads to economic and food security risks throughout the world because of its major influences on agriculture. Accurate forecasts of climate 3–6 months ahead of time can potentially allow farmers and others in agriculture to make decisions to reduce unwanted impacts or take advantage of expected favorable climate. However, potential benefits of climate forecasts vary considerably because of many physical, biological, economic, social, and political factors. The purpose of this study was to estimate the potential economic value of climate forecasts for farm scale management decisions in one location in the Southeast USA (Tifton, GA; 31°23′N; 83°31′W) for comparison with previously-derived results for the Pampas region of Argentina. The same crops are grown in both regions but at different times of the year. First, the expected value of tailoring crop mix to El Niño-Southern Oscillation (ENSO) phases for a typical farm in Tifton was estimated using crop models and historical daily weather data. Secondly, the potential values for adjusting management of maize (*Zea maize* L.) to different types of climate forecasts (perfect knowledge of (a) ENSO phase, (b) growing season rainfall categories, and (c) daily weather) were estimated for Tifton and Pergamino, Argentina (33°55′S; 60°33′W). Predicted benefits to the farm of adjusting crop mix to ENSO phase averaged from US$ 3 to 6 ha^{-1} over all years, depending on the farmer's initial wealth and aversion to risk. Values calculated for Argentina were US$ 9–15 for Pergamino and up to US$ 35 for other locations in the Pampas. Varying maize management by ENSO phase resulted in predicted forecast values of US$ 13 and 15 for Tifton and Pergamino, respectively. The potential value of perfect seasonal forecasts of rainfall tercile on maize profit was higher than for ENSO-based forecasts in both regions (by 28% in Tifton and 70% in Pergamino). Perfect knowledge of daily weather over the next season provided an upper limit on expected value of about US$ 190 ha^{-1} for both regions. Considering the large areas of field crop production in these regions, the estimated economic potential is very high. However, there are a number of challenges to realize these benefits. These challenges are generally related to the uncertainty of climate forecasts and to the complexities of agricultural systems.

Keywords: Climate prediction; Crop models; Forecast value; Optimal management; El Niño; La Niña

1. Introduction

Agriculture is highly vulnerable to year-to-year climate variability. One reason that climatic variability is often so devastating to agriculture is that we do not know what to expect in the next growing season. Thus, farmers and other decision makers in agriculture, unprepared for the weather conditions that do occur, make decisions based on their understanding of general climate patterns for their regions. Climatic uncertainty often leads to conservative strategies that sacrifice some productivity to reduce the risk of losses in poor years. If better predictions of climate were available three to six months ahead of time, it may be possible to modify decisions to decrease unwanted impacts and to take advantage of expected favorable conditions.

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PII: S0167-8809(00)00225-5

Advances in our understanding of interactions between the tropical oceans and the atmosphere, our ability to monitor these systems, and the speed and cost of computers now allow predictions of climate variations with useful skill several months ahead of time in many parts of the world (Barnston et al., 1994; Latif et al., 1994, 1998; Chen et al., 1995; National Research Council, 1996). Most current climate forecasts are based in some way on the El Niño-Southern Oscillation (ENSO). ENSO refers to shifts in surface temperatures (SST) in the eastern equatorial Pacific and related shifts in barometric pressure gradients and wind patterns in the tropical Pacific (the Southern Oscillation). ENSO activity is characterized by warm (El Niño), neutral, or cool (La Niña) phases identified by SST anomalies. Although the ENSO phenomenon occurs within the tropical Pacific, it affects interannual weather variability across much of the globe (Ropelewski and Halpert, 1987, 1996; Kiladiz and Diaz, 1989).

Researchers have shown high correlation between ENSO activity and agricultural production in many parts of the world (Nichols, 1985; Handler, 1990; Garnett and Khandekar, 1992; Cane et al., 1994; Rosenzweig, 1994; Carlson et al., 1996; Rao et al., 1997; Hansen et al., 1998a,b, 1999; Podestá et al., 1999b). The predictability of climate and its influence on crop production suggests that agricultural applications of climate forecasts may be highly valuable to society. Cusack (1983) and Sah (1987) suggested that climate prediction could lead to the next 'Green Revolution.' In spite of the optimism, a gap exists between the production of climate forecasts and their practical use in agricultural decision making. A common perception is that advances in seasonal climate prediction will alone be enough for societal benefits to accrue. However, simply documenting the effects of climate variability and providing better climate forecasts to potential users are not sufficient. Other elements, such as the existence of feasible alternatives for adaptive actions in response to climate forecasts, must be understood for society to benefit. Current climate forecasts do not provide such information to the agricultural sector. Because of the biophysical, societal, and institutional complexities of agricultural systems, comprehensive research programs are needed to bridge the gap that now exists between climate forecasts and their routine applications in agriculture (Podestá et al., 1999a).

1.1. Previous work in Argentina

A multi-institutional, interdisciplinary research program was initiated by a consortium of universities in Florida (Podestá et al., 1999a), including climatologists, agricultural scientists, social scientists, and various agricultural decision makers, to assess the potential for climate prediction applications in the Pampas region of Argentina. This region is characterized by high interannual variability of rainfall and rainfed crop production (Hall et al., 1992). Land allocated to wheat, maize, soybean and sunflower accounted for 90% of total land devoted to agriculture in the Pampas, producing grain for a value of US$ 5 billion (SAGPyA, 1994). ENSO exerts a highly significant influence on climate in the Pampas (Ropelewski and Halpert, 1987; Kiladiz and Diaz, 1989; Magrin et al., 1998; Podestá et al., 1999b). Average monthly rainfall amounts from November to April were higher (lower) in El Niño (La Niña) years when compared with neutral years or with long-term climatology. By analyzing historical crop reporting district data, it was found that maize (*Zea maize* L.) and sorghum (*Sorghum bicolor* (L.) Moench) yield anomalies were significantly higher (lower) during El Niño (La Niña) events (Podestá et al., 1999a). Soybean (*Glycine max* (L.) Merr.) yields were lower and sunflower (*Hellianthus annuus* L.) yields higher in La Niña events. ENSO phase did not significantly affect wheat, the only winter crop. These responses to ENSO can be explained in part by the seasonal patterns of rainfall relative to each cropping season, as shown in Fig. 1 for Pergamino. In this figure, the year starts with July before the period of peak ENSO activity (October through March) to show how major crop growing seasons relate to the timing of ENSO effects. The strong effect of ENSO on maize yield is due to the growing season for maize coinciding with the time of year when ENSO effects on precipitation are strongest.

Crop simulation models, calibrated and tested for the Pampas region (Meira and Guevara, 1997; Magrin et al., 1998; Guevara et al., 1999; Meira et al., 1999), were used to explore optimal crop management for each ENSO phase. An optimization algorithm was adapted for use with crop models to explore optimal management at a field scale, taking into account economic returns and risk (Royce et al., 2000). Because farmers indicated that they might change the

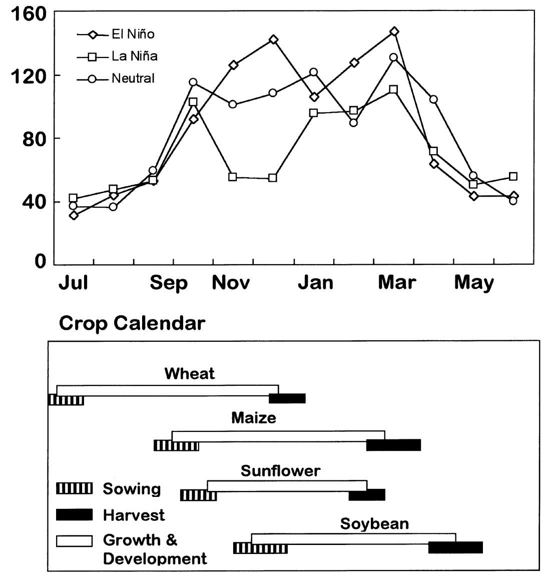

Fig. 1. Monthly mean precipitation (mm) by ENSO phase for Pergamino, Argentina based on historical data from 1931 through 1996 (top). Crop calendars shown below for wheat, maize, sunflower, and soybean include growing seasons as well as planting and harvesting periods.

proportion of crops they plant depending on ENSO phase, Messina (1999) and Messina et al. (1999) developed a non-linear optimization model to determine the best crop mix (area sown to each crop), taking into account farmers' risk attitudes. They found that the economic value of modifying crop mix was between US\$10 and 15 ha^{-1} in Pergamino and about US\$ 35 ha^{-1} in Pilar, a location with lower rainfall amounts. These expected values depended on several factors, including current prices, the preceding crop and ENSO phase, and farmers' risk aversion. Their study assumed that current management practices would be used for each crop, thus there is potential for combining crop mix and management to achieve additional gains in economic value in this region.

These original studies suggest that the potential value for climate prediction application to agriculture in the Pampas region of Argentina is indeed very high. In 1998–1999, about 11.1 million ha of land was used to produce soybean and maize. If one assumes an average value of US\$ 15 ha^{-1} by using climate forecasts to modify crop mix, crop management, or both for these two crops alone, the expected potential value would average about US\$ 166 million per year in this region. Although the regional value of climate forecasts will depend on many factors not yet analyzed, this extrapolation provides a rough estimate of its order of magnitude. Research is still on-going to determine how farmers respond to this information and whether the potential can actually be realized.

1.2. Previous work in the Southeast US

ENSO activity also affects climate in the southeastern USA (Ropelewski and Halpert, 1986, 1987, 1996; Rogers, 1988; Kiladiz and Diaz, 1989; Sittel, 1994; Green et al., 1997). In this region, El Niño events are characterized by lower winter temperatures than neutral or La Niña events. Precipitation is higher in the Gulf Coast states in the winter and throughout the region by spring during El Niño events. In the summer, climate impacts of El Niño events are more localized, including drier conditions along the Atlantic Coast and from north Texas to northern Alabama. With some exceptions, La Niña events show the reverse of the climate anomalies associated with El Niño events. They include above-average temperatures east of the Mississippi River in the winter and in Georgia, northern Florida, and South Carolina in the spring. Effects in the summer are weaker and more variable spatially.

Agriculture is one of the most important sectors of this region's economy, contributing about US\$ 33 billion in 1997, with crop production valued at about US\$ 14 billion (USDA, 1997). In North America, the summer cropping season does not coincide with the strongest ENSO signal. However, by analyzing historical crop yields, we found that ENSO significantly influenced maize, wheat (*Triticum aestivum* L.), cotton (*Gossipium hirsutum* L.), tomato (*Lycopersicon* spp.), rice (*Oryza sativa* L.), sugarcane (*Saccharum officinarum* L.) and hay in eight southeastern states (Hansen et al., 2000). ENSO phase explained a shift of US\$ 212 million, or 26% of the long-term average, inflation adjusted value of maize and US\$ 133 million, or 18% for soybean in a four-state region (Hansen et al., 1998a). We also found that ENSO influenced high value crops in Florida, such as *Citrus* spp., tomato, bell pepper (*Capsicum annuum*), snap beans (*Phaseolus* spp.), and sweet corn (Hansen et al., 1998b,c). Adams et al. (1995) estimated that the value of improved forecasts for agriculture in the southeastern US might exceed

US$ 100 million annually, less than 0.5% of the value of crops produced annually in this region. Research is needed to determine how much, if any, of these variations in agricultural production value can be recovered through decisions tailored to climate forecasts.

1.3. Objectives

Because summer crop production in the SE USA is out of phase with the time when ENSO effects on climate are greatest, it was hypothesized that the potential value of climate forecasts for crop production would be lower in this region than in Argentina. A study was undertaken to estimate the potential value of ENSO-based climate forecasts for changing crop and farm management decisions in one location in the Southeast USA for comparison with previously derived results for the Pampas region. A site was selected in the Coastal Plain of Georgia (Tifton) to study the potential value of climate forecasts to agriculture. Results for this site were compared with those from similar studies for Pergamino, located in the heart of the Argentine Pampas. First, the expected value of changing crop mix for a typical farm in this region was estimated to compare with results obtained by Messina et al. (1999). Secondly, the potential value for adjusting management of maize to different types of climate forecasts was estimated for both Tifton and Pergamino. In this part of the study, the potential value of using perfect knowledge of ENSO phase, perfect knowledge about whether the coming year would be in the top, middle, or lower one-third rainfall seasons, and perfect knowledge of daily weather for the season were compared. Comparisons of results across the two regions are provided.

2. Methods

Regionally adapted and tested crop simulation models can quickly reveal the impacts of a wide range of decision alternatives under a wide range of weather conditions. Given the high cost of long-term field experiments and the long delay before results are available for a sufficient range of weather conditions, crop simulation is the only feasible way to examine the interaction between climate variability, management decisions, and crop yields. We combined crop simulation models and simple economic decision models to examine the potential benefits of tailoring crop production decisions to ENSO phases. The present study focuses on Tifton, Georgia, as a case study of the Southeast US. Tifton is a humid region with sandy soils. The main crops are peanut, maize, soybean, cotton and wheat grown either under rainfed or irrigated conditions (USDA, 1997). Results from this site were then compared with those from similar studies in Pergamino, Argentina. Pergamino results for the farm scale crop mix problem were published by Messina et al. (1999), whereas options for maize management for this location were analyzed in this study for comparison with Tifton.

2.1. Climate data

ENSO events were categorized by the Japan Meteorological Agency definition based on five-month running means of spatially-averaged sea surface temperature (SST) anomalies in the region of the tropical Pacific Ocean between 4EN-4ES and 90E-150EW. A crop year for the Tifton site (October through September) was classified as El Niño (La Niña) if the SST anomalies were $\geq 0.5°C$ ($\leq -0.5°C$) for at least six consecutive months including October through December (Sittel, 1994; Trenberth, 1997). The SST index is based on observed data for the period 1949 to the present. For years before 1949, the index was derived from reconstructed monthly mean SST fields (Meyers et al., 1999). The period 1922 to 1998 includes 15 El Niño (1926, 30, 41, 52, 58, 64, 66, 70, 73, 77, 83, 87, 88, 92, 98) and 16 La Niña events (1923, 25, 39, 43, 45, 50, 55, 56, 57, 65, 68, 71, 72, 74, 76, 89).

Daily weather data (maximum and minimum temperature, precipitation, and solar irradiance) for Tifton are from the National Climatic Data Center Summary of the Day data base (EarthInfo, 1996) for 1922 to 1990, and from the Georgia Automated Environmental Monitoring Network (Hoogenboom and Gresham, 1997) for 1991–1997. Solar irradiance data missing prior to 1991 were generated stochastically (Hansen, 1999). Soil parameters for a fine-loamy, siliceous, thermic Plinthic Paleudults soil at Tifton were obtained from Mavromatis et al. (2000). Pergamino daily weather data (1937–1997) are from the Servicio Meteorologico Nacional, and have undergone extensive quality checking (Podestá, University of Miami,

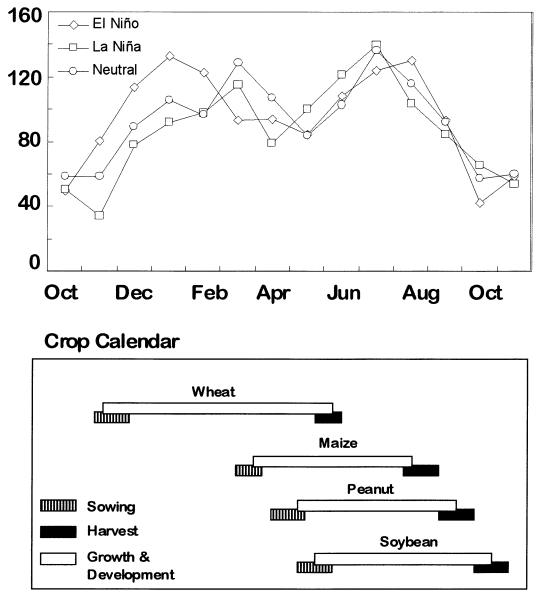

Fig. 2. Monthly mean precipitation by ENSO phase for Tifton, Georgia (USA) based on historical data from 1922 through 1998. Crop calendars shown for wheat, maize, peanut, and soybean include growing seasons as well as planting and harvesting periods.

personal communication). Missing solar irradiance was either estimated from available bright sunshine duration, with monthly slope and intercept coefficients of the Ångström (1924) equation estimated by robust regression (Lanzante, 1996), or generated stochastically (Hansen, 1999). Data of 6 years (1954, 1955, 1956, 1964, 1965, and 1966) were discarded from analyses due to gaps during the growing season. Fig. 2 shows seasonal distribution of rainfall for each ENSO phase along with the crop calendars for the main crops.

2.2. Optimal crop mix

Messina et al. (1999) used crop simulation linked to an economic optimization model to explore the potential benefits of tailoring farm-scale crop mix to ENSO phases for two locations in the Pampas of Argentina. The model identifies the crop mix that maximizes expected utility of wealth based on given costs and prices, risk preferences, and crop yields simulated for each of a given set of weather years (Lambert and McCarl, 1985). It assumes that farmers allocate land among cropping enterprises in a way that maximizes the expected utility of wealth at the end of a 1-year planning period (W_F) for given expected weather conditions

$$\max_{\boldsymbol{x}} E\{U(W_F)\} = \sum_{i=1}^{n} U(W_0 + \sum_{j=1}^{m} \boldsymbol{x}_j \boldsymbol{\pi}_{ij}))/n$$

$$\text{subject to}: \boldsymbol{Ax} \leq \boldsymbol{b}, \quad \boldsymbol{x} \geq 0, \tag{1}$$

where U is utility for climate year i, W_0 is initial wealth, $\boldsymbol{x}$ is the vector of areas allocated to each crop enterprise x_j, π_{ij} is net returns for crop j and year i, n denotes the number of years, m the number of crop enterprises, $\boldsymbol{A}$ is a matrix of technical coefficients and $\boldsymbol{b}$ is a vector of farm resource constraints b_k. Technical coefficients in matrix $\boldsymbol{A}$ are 1s and 0s to select crop enterprises that use the limiting resource b_k (e.g. irrigation and labor). Net returns, $\boldsymbol{\pi}_{ij}$, from the jth crop enterprise are calculated from constant production costs and prices, and yields simulated using the ith weather year. Aversion to risk is encapsulated in the degree of curvature of a nonlinear utility function U which depends on farmer wealth W. The power function

$$U(W_F) = \frac{W_F^{1-R_r}}{1-R_r} \tag{2}$$

used in this study implies constant relative risk aversion R_r, and decreasing absolute risk aversion with increasing initial wealth (Hardaker et al., 1997). Calculation of expected utility for a given crop mix and climate expectation is based on distributions of yields of each crop predicted by the DSSAT crop simulation models (Jones et al., 1998) using historic daily weather data.

Available data and characteristics of farming systems in southern Georgia required some differences from the model implementation described in Messina et al. (1999). First, initial wealth was estimated from reported equity instead of land value. Second, farm fixed costs (i.e. overhead and taxes) were factored into available crop enterprise budgets on a per-ha basis in proportion to the contribution of each enterprise to total income (USDA/ERS, 1999a). This information is based on accepted farm surveys, but may introduce small errors in the estimates of fixed costs. Third, in the present study, it was assumed that irrigation is available on a fraction of the farm. Finally, favor-

Table 1
Representative crop management practices used for crop mix optimization, Tifton, GA

	Cultivar	Sowing date	Density (pl m^{-2})	Row spacing (cm)	N fertilization			
					First application		Second application	
					DAS[a]	(kg ha^{-1})	DAS	(kg ha^{-1})
Soybean	Bragg	7 June	23	91	0	6	–	–
Maize	McCurdy 84aa	2 April	5[b]	75	0	70	42	70
Peanut	Florunner	8 May	12.6	91	0	7	–	–
Wheat	Florida 302	25 November	330	17	10	27	51	100

[a] Days after sowing.
[b] Density increased to seven plants m^{-2} for irrigated crop.

able support prices apply to a limited quota of peanut production.

The study considered four crops: maize, wheat, soybean and peanuts. Table 1 shows management assumptions used for the simulations. Each crop was simulated for both rainfed and irrigated conditions for each year of historic weather data. The crop models overestimated mean farm yields in the surrounding county (USDA/ERS, 1999b). Simulated yields were therefore adjusted to match county mean yields. For peanut and soybean, a soil fertility factor of 0.65 was used to correct the bias. Simulated maize and wheat yields were multiplied by the ratio of mean observed to simulated yields.

Assumptions about the case study were based on survey information from the National Agricultural Statistics Service (NASS) and the Economic Research Service (ERS). Constraints in $\boldsymbol{b}$ (Eq. (1)) include a farm size of 279 ha, a maximum of 26% of total land area that can be irrigated, and a peanut quota of 130 Mg (USDA/ERS, 1994). Initial farm equity (US$ 314,900) and mean farmgate prices and production costs (Table 2) are from USDA/ERS (1999c). Irrigation costs (US$ 0.24 mm^{-1} ha^{-1}) were calculated from the amount of water applied to the crop. The price of urea was US$ 0.63 kg^{-1} N.

Table 2
Mean crop prices and production costs used for crop mix optimization, Tifton, GA

Crop	Price (US$ Mg^{-1})	Cost (US$ ha^{-1})
Soybean	222	282
Maize	101	364
Peanut (quota)	634	1053
Peanut (non-quota)	132	1053
Wheat	120	260

Model-based analyses of decisions for hypothetical farms necessarily entail many assumptions that are difficult to verify and that may impact results substantially. We therefore analyzed the sensitivity of predicted optimal crop mix and potential information value to risk aversion, initial wealth, crop prices and production costs. The optimization problem (Eq. (1)) was solved for three levels of relative risk aversion (R_r = 0, 2 and 3) and two levels of initial wealth (W_0 = equity and W_0 = 0.5 equity) given mean prices and production costs. The same procedure was applied for nine crop-price and four production-cost scenarios that reflect price variations in recent years ($R_r = 2$; W_0 = equity).

2.3. Optimal maize management practices

Early proponents of crop simulation models envisioned the routine use of nonlinear search algorithms to identify optimal management (Dent and Blackie, 1979). However, the relatively-efficient gradient- and direct-search algorithms that have sometimes been employed can produce incorrect results for response surfaces that have discontinuities or multiple local optima-typical of crop and other dynamic agricultural simulation models (Mayer et al., 1996). Yield response to the timing of management events (e.g., planting) can be particularly problematic. Simulated annealing algorithms have proven to be robust at identifying global optima of poorly behaved response surfaces (Goffe et al., 1994; Press et al., 1986; Ingber, 1996), including agricultural simulation models (Mayer et al., 1996, 1998). Royce et al. (2000) linked

Table 3
Range of management variables used for optimizing maize management practices at Tifton and Pergamino

	Planting			N applications		
	Dates		Density (m^{-2})	Amounts ($kg\,ha^{-1}$)	Dates (DAP)	
	Tifton	Pergamino			Second	Third
Initial	15 April	27 October	8.5	40	14	35
Minimum	1 March	1 September	4.5	0	2	28
Maximum	5 May	10 November	12.5	180	27	42

the relatively efficient adaptive simulated annealing algorithm of Ingber (1996) with the DSSAT family of crop models (Jones et al., 1998) to identify management strategies that maximize expected net returns. The resulting optimizer was used to identify combinations of maize hybrid, planting date, planting density, and the amount and timing of up to three nitrogen fertilizer applications (the first constrained to immediately follow planting) that maximize expected gross margins (i.e. income minus variable costs). Table 3 gives the range of each management variable considered for maize in Tifton and Pergamino.

The concept of a ‘perfect’ seasonal forecast is used frequently, but is rather ambiguous. It is useful for separating uncertainty caused by inherent weather variability from that caused by an imperfect forecast. A perfect categorical forecast (e.g. ENSO phase; above normal, normal or below normal rainfall forecasts, which are referred to as tercile categories) generally contains less information than a perfect continuous forecast (e.g. daily or monthly precipitation). For maize at Tifton and Pergamino, we consider three types of perfect forecast: perfect knowledge of ENSO phases, perfect knowledge of seasonal precipitation tercile categories, and perfect knowledge of daily weather throughout the season. Perfect knowledge of ENSO phase was mimicked by dividing the years according to ENSO phase. To examine the potential benefits of perfect seasonal categorical precipitation forecasts, we grouped weather data into three classes. Years with low, moderate and high precipitation during the growing season were identified by sorting years by total May–July (Tifton) or November–January (Pergamino) precipitation. For Pergamino, each category included 18 years. Because the number of years (50) used for Tifton is not evenly divisible by 3, the dry and wet categories each contained 16 years, and the moderate category 18 years. Finally, optimizing management for each individual year allowed us to characterize the upper limit of the value of perfect advanced knowledge of daily weather.

2.4. Potential forecast value

Optimal strategies derived from crop models can provide first-order estimates of the potential value of use of climate forecasts. The potential value V of a climate forecast can be expressed as the difference in expected economic returns to optimal decisions conditioned on ENSO phases and returns to optimal decisions based on the historical climatology (e.g. Thornton and MacRobert, 1994; Mjelde and Hill, 1999). For annual decisions evaluated across n years

$$V = \sum_{i=1}^{n} (\boldsymbol{\pi}_i(\boldsymbol{x}^*|F_i) - \boldsymbol{\pi}_i(\boldsymbol{x}^*|H))/n \qquad (3)$$

where $\boldsymbol{\pi}_i(\boldsymbol{x}^*|F_i)$ and $\boldsymbol{\pi}_i(\boldsymbol{x}^*|H)$ are net income (farm total or ha^{-1}) in year i as a function of the vector of management variables $\boldsymbol{x}$ optimized for either the current forecast F_i or the historic climatology H. For the optimal crop management problem, $\boldsymbol{x}$ consists of all combinations of crop management variables (e.g. planting date, variety, N application), whereas $\boldsymbol{x}$ is area allocated to each crop for the farm scale optimal crop mix problem.

3. Results and discussion

3.1. Value of climate forecasts for crop mix

Fig. 3 shows optimal crop mix predicted for Tifton for each ENSO phase, at three levels of risk aversion.

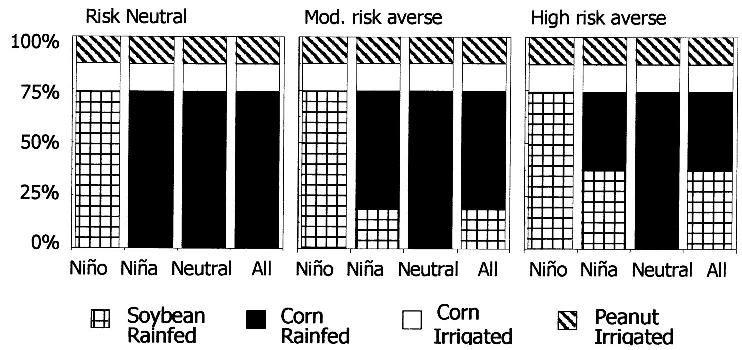

Fig. 3. Optimal land allocation by ENSO phase and three levels of risk aversion: Risk neutral ($R_r = 0.0$; W_0 = equity), moderately risk averse ($R_r = 3.0$; W_0 = equity) and very risk averse farmers ($R_r = 3.0$; $W_0 = 0.5$ equity).

ENSO influenced only the mix of rainfed crops. These changes can be explained by the timing of ENSO effects on rainfall (Fig. 2), and the relative sensitivity of maize and soybean to those effects. The direction of yield response to ENSO was opposite for maize and soybean. Higher simulated maize yields during La Niña were associated with increased precipitation in June when grain number is determined. Higher simulated soybean yields during El Niño were associated with increased rainfall in August during early pod formation. ENSO effects on yields and crop mix were generally opposite of those predicted for Pergamino (Messina et al., 1999).

Irrigation moderates the effects of climate variability on crop yields. Therefore, net returns for irrigated crops did not vary among ENSO phases (Table 4). The constraint on peanut production at the support price, and the insensitivity of the irrigated crops to ENSO explain the constant proportion of land allocated to irrigated peanut and maize crops (Fig. 3). Irrigated peanut at the quota price had the highest net return for all ENSO phases, followed by maize.

Table 4
Mean net returns (US\$ ha^{-1}) by ENSO phase and crop enterprise for the Tifton, GA location

Crop	Mean net returns (US\$ ha^{-1})		
	All years	La Niña	El Niño
Rainfed			
Soybean	142	136	165
Maize	161	185	146
Peanut	572	668	572
Wheat	58	72	34
Irrigated			
Soybean	229	235	225
Maize	439	470	422
Peanut	1505	1533	1457
Wheat	191	188	191

Constraints to the areas of irrigated maize and quota peanut production — the most profitable crops (Table 4) — imposed some diversification even under the assumption of risk neutrality (Fig. 3). As expected from theory and previous studies (e.g. Kingwell, 1994; Messina et al., 1999), crop diversification increased with risk aversion. Mean farm net returns decreased from US\$ 98.87 ($R_r = 0$; W_0 = equity) to 95.59 ($R_r = 3$; $W_0 = 0.5$ equity) with increasing risk aversion, and variability in net returns (standard deviations) decreased from US\$ 33.91 to 21.82. Increasing crop diversification with increasing risk aversion is consistent with results in Argentina (Messina et al., 1999) and Australia (Kingwell, 1994).

Forecast value increased with increasing risk aversion, particularly at the lower initial wealth (Fig. 4). Crop mix and forecast value did not vary within the range of risk aversion considered (R_r = 0–2) when initial wealth was equal to equity. However, when initial wealth was reduced to a half of equity, each increment of R_r changed crop mix and increased forecast value. For a decision maker with a given relative risk aversion, Eq. (3) implies that absolute risk aversion increases as expected wealth decreases. Increasing risk aversion increased the differences between the crop mix optimized for all years and for each ENSO phase, and therefore the flexibility to make use of the

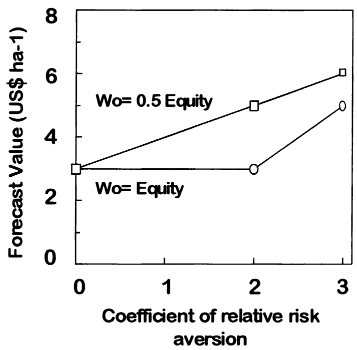

Fig. 4. Predicted value of ENSO information as a function of relative risk aversion and initial wealth.

ENSO information. Our results highlight the importance of initial wealth as a determinant of potential changes in land allocation in response to climate forecasts. The increase in forecast value with increasing risk aversion was accompanied by reduction of mean income with increasing risk in the absence of ENSO information. Mjelde and Cochran (1988) and Messina et al. (1999) also showed positive association between risk aversion and the value of climate information for crop mix or management under normally favorable climate regimes in Illinois and Argentina.

Although results were similar to those obtained by Messina et al. (1999) in Argentina, potential values of ENSO-based climate forecasts were lower in Tifton for each level of risk aversion. For a moderate level of risk aversion ($R_r = 2$), the potential value of ENSO-based forecasts was US$ 3 ha^{-1} in Tifton, whereas it was US$ 11 for Pergamino and US$ 35 for Pilar, Argentina. When initial wealth was assumed to be only half of farm equity, the forecast value increased in Tifton to about US$ 5 ha^{-1} compared with US$ 15 ha^{-1} for Pergamino.

Changes in relative costs and prices can favor or exclude crops from the feasible set of options. An increase in the price or a reduction of production costs of one crop relative to others can exclude the other crops from the feasible set of options. Prices or production costs can therefore constrain potential changes of land allocation under a climate forecast, thereby decreasing or even eliminating the potential value of the forecast. This was the case when 1991, 1993 and 1997 crop prices were used. Higher prices for either maize or soybean led to monocultures under rainfed conditions for all ENSO phases (Table 5). In contrast, the balance among crop prices for 1990 and 1992 favored diversification and increased the potential value of ENSO-based forecasts. These results confirm previous findings for the Pampas, and highlight the importance of careful evaluation of current price expectations in assessing the value of climate forecasts in a particular year.

Table 5
Forecast value V under different analog production cost scenarios for rainfed crops and for a moderately risk averse farmer ($R_r = 2$)

Year	Prices as percent of 1992–97 mean				V (US$ ha^{-1})
	Soybean	Maize	Peanut	Wheat	
Production cost scenarios					
1994	104	105	97	91	5.83
1995	105	113	100	98	4.79
1996	109	109	100	104	5.39
1997	172	208	156	171	5.67
Crop price scenarios					
1989	94	95	94	111	4.20
1990	96	94	118	95	6.17
1991	92	97	94	76	0.04
1992	88	88	104	98	5.53
1993	105	93	104	82	0.94
1994	89	88	97	88	4.23
1995	108	113	101	105	1.59
1996	115	128	94	134	0.67
1997	115	105	94	111	4.97

3.2. Value of climate forecasts for maize management

Optimal management and expected maize yields varied under different climate forecasts for the two locations. Expected yields in Tifton averaged 8.41, 8.60, 8.58, and 10.65 Mg ha^{-1} for management optimized for all years and by ENSO phase, terciles, and actual daily weather data, respectively (Table 6). Corresponding values for Pergamino were 7.96, 8.36, 8.27, and 10.26 Mg ha^{-1} (Table 7). Increases in yield and margins were higher for Pergamino than Tifton (Tables 6 and 7). In spite of substantial differences in the strength and nature of the ENSO signal between Tifton and Pergamino, the potential value of each type of 'perfect' seasonal forecast was quite similar between the two locations in our study (Table 8). Maize yields in Georgia and much of the Southeast US tend to be higher than normal in La

Table 6
Optimal maize management and expected outcomes for various climate forecast types, Tifton, GA

Years	n	Planting		Total N applied (kg ha^{-1})	Expected:	
		Date	Density (m^{-2})		Yield (Mg ha^{-1})	Margin (US$ ha^{-1})
Optimized for all years						
All	50	4 May	6.8	146	8.41	798
Optimized by ENSO phase						
El Niño	11	30 April	6.8	149	8.32	780
Neutral	27	5 May	6.8	140	7.97	752
La Niña	12	4 May	8.0	166	10.26	972
Average	50	4 May	7.1	148	8.60	811
Optimized by precipitation terciles						
Dry	16	2 May	5.2	115	6.47	607
Moderate	18	29 April	7.8	150	9.46	899
Wet	16	4 May	7.6	154	9.71	927
Average	50	2 May	6.9	140	8.58	815
Optimized for actual daily weather						
Average	50	8 April	11.2	167	10.65	989

Table 7
Optimal maize management and expected outcomes for various climate forecast types, Pergamino, Argentina

Years	n	Planting		Total N applied (kg ha^{-1})	Expected	
		Date	Density (m^{-2})		Yield (Mg ha^{-1})	Margin (US$ ha^{-1})
Optimized for all years						
All	54	10 November	7.0	99	7.96	630
Optimized by ENSO phase						
El Niño	11	2 November	8.2	188	10.43	807
Neutral	32	10 November	7.0	95	7.98	628
La Niña	11	10 November	11.0	60	7.38	532
Average	54	8 November	8.1	107	8.36	645
Optimized by precipitation terciles						
Dry	18	8 November	4.5	41	4.97	401
Moderate	18	10 November	6.8	96	7.97	629
Wet	18	9 November	10.2	148	11.87	937
Average	54	9 November	7.2	95	8.27	655
Optimized for actual daily weather						
Average	54	20 October	9.5	78	10.26	822

Table 8
Value (US$ ha^{-1}) of optimal use of various types of perfect seasonal forecast for maize management

Location	ENSO phases	Rain terciles	Daily weather
Tifton	13.02	16.66	191.34
Pergamino	15.14	25.80	190.82

Niña years and lower than normal in El Niño years (Hansen et al., 1998a, 2000). In La Niña years, maize near Tifton benefits from significantly more rainfall in June coinciding with tasseling, when final yield is most vulnerable to water stress (Hansen et al., 1998a). Much of the benefit of tailoring maize management to ENSO phases results from increasing planting density and N fertilizer application to take

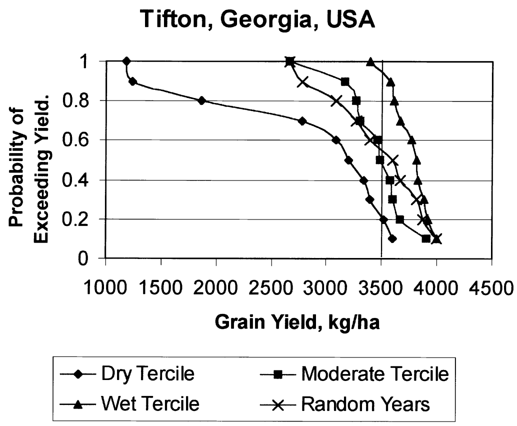

Fig. 5. Probabilities of exceeding maize yields at Tifton for each tercile of weather category as well as for all (random) years. Results are based on simulated maize yields using 1922–1998 weather data. Vertical line is used to show differences in probabilities of yield exceeding 3500 kg/ha among tercile weather and random years.

advantage of more favorable moisture during La Niña (Fig. 4).

As expected, the potential value of information increased from perfect knowledge of ENSO phases to precipitation terciles of future daily weather. Simulated yield variability was reduced considerably under each of the climate prediction scenarios. Fig. 5 shows probabilities of exceeding given yield values for all years, and when management practices were optimized for each ENSO phase (a), for each tercile (b), and under perfect knowledge of daily weather (c). This figure demonstrates that not all yield variability can be eliminated under any climate prediction method, even under perfect knowledge of daily weather. Perfect knowledge of current or preceding ENSO phase is realistic for decisions made after about October or November. It also serves as a minimum baseline level of prediction skill. Predictions based on statistical models or dynamic, coupled ocean-atmospheric models must exceed the skill of ENSO phases to be advantageous. Perfect forecasts of seasonal precipitation tercile categories are not possible.

Although efforts are underway to improve and evaluate seasonal forecasts of precipitation tercile categories, the marginal value of even perfect precipitation tercile forecasts was fairly small (28% more than the value of ENSO phases) for maize management at Tifton. The marginal value of precipitation tercile forecasts relative to ENSO phases (about 70%) was higher at Pergamino even though the ENSO signal in growing-season precipitation is stronger at Pergamino than at Tifton. A large gap exists between the potential value of perfect categorical forecasts of either ENSO phases or precipitation and the potential value of perfect foreknowledge of daily weather. Much of the benefit predicted for optimal use of daily weather apparently came from adjusting planting date to avoid water stress during the critical period after anthesis when grain number is determined. Given the inherent unpredictability of the timing of precipitation past a few days, the gap between the best climate forecasts and perfect foreknowledge of daily weather will likely remain large.

4. Challenges to realizing potential benefits of climate forecasts

The potential value of tailoring crop mix and/or management practices for two crops (maize and soybean) to ENSO phase in the Pampas region was estimated to be on the order of US$ 166 million per year. More than one million ha of these two crops are grown annually in four Southeast US states (Georgia, Alabama, Florida and South Carolina) (NASS, 1997). If farmers could gain US$ 5–10 ha^{-1} from the use of ENSO-based climate forecasts, this region might expect to increase farm income by an average of US$ 5–10 million per year. This is much less than the potential US$ 100 million annual value of optimal use of improved climate forecasts for agriculture in the Southeast US estimated by Adams et al. (1995). These rough estimates are based on presumably very simple adjustments to crop management. Many more agricultural decisions may benefit from the use of climate forecasts (Hildebrand et al., 1999). However, difficult challenges arising from uncertainties of climate forecasts and complexities of agricultural systems must be overcome before potential benefits of climate forecasts to agriculture can be fully realized.

4.1. Uncertainty of climate forecasts

Seasonal climate forecasts are inherently uncertain. Reasons for the uncertainties include the chaotic nature of atmospheric dynamics, imperfect understanding and representation of the physics of the ocean-atmosphere system, inadequate monitoring of ocean conditions (particularly outside of the tropical Pacific), and problems with current data assimilation techniques (Cane and Arkin, 1999). Because some of the uncertainties will always remain regardless of improvements in prediction technology, climate forecasts are best interpreted as shifts in the probability distributions that characterize a local climate. Economic risk theory can handle forecast uncertainty. However, to use forecasts effectively, farmers must integrate their perceptions of forecast uncertainty with many other types of information in the context of their goals, abilities, constraints and risk tolerance as they manage their production systems. Before they will use forecasts, agricultural decision makers need and want to know how reliable they are, how they might benefit from their use, and the consequences of decisions when forecasts are not accurate in a particular year. There may be potential benefits for farmers to use real-time simulation, with current weather up to the current day followed by updated climate forecasts for the future, to take advantage of improved accuracy in forecasts over time. Few farmers will risk a trial-and-error approach to learn how to apply climate forecasts because of the economic risks involved, the multiplicity of current forecast products (each with its own characteristics), and the rapid pace of development in this field that could render forecast-based management strategies obsolete by the time they develop them.

Objective measures of climate forecast uncertainty can be difficult to obtain, particularly for consensus forecasts that incorporate subjective judgement. The interactive effects of location, lead time, spatial and temporal scales, and decadal-scale climate variability further complicate attempts to characterize the uncertainty of climate forecasts.

If objective measures of forecast uncertainties are available, communicating them to decision makers remains a challenge. Due to several types of 'cognitive illusion' most people find it difficult to correctly perceive and process probabilistic climate forecasts (Nichols, 1999). We have encountered examples of both overestimation and underestimation of the uncertainties associated with ENSO-based forecasts. Farmers and extension agents interviewed in the southeast US expressed some doubt regarding the relevance of ENSO to local climate, and the feasibility of climate forecasts themselves. Some of the skepticism seems to be due to confusion of weather and climate and the importance that they placed on forecasts of weather events, such as freezes and hurricanes (Hildebrand et al., 1999). An essentially determinist mental model (Weber, 1997) of weather events that either do or do not occur as predicted may lead to inadequate appreciation and improper interpretation of the probabilistic nature of longer-term climate forecasts. In some instances, the popular media reinforced a deterministic interpretation of climate forecasts by ignoring or under emphasizing the uncertainties inherent in expected results of the recent El Niño and La Niña events. Interviews with farmers on the Argentine Pampas regarding the use of climate forecasts revealed a shift from skepticism prior to the 1997–1998 El Niño event, to enthusiastic acceptance after the predictions associated with that event were confirmed. Predictions based on the La Niña of 1998–1999 missed the mark, however, and disillusionment with climate prediction became widespread (Magrin et al., 2000).

Interactions with farmers and extension agents in both regions underscore two important lessons about communicating forecast uncertainties. First, although farmers understand and contend regularly with the uncertain nature of the climate, researchers need to work with farmers to develop a common language for communicating probabilistic climate information. Second, effective communication of climatic or any other new information is best accomplished through providers of information and advice that farmers already know and trust.

4.2. Complexity of agricultural systems

Agriculture is extensive; it includes thousands of farmers in most regions. Each is an independent decision maker operating within his or her own social, economic, natural resource, and political environment. They obtain information and material from a number of sources, usually manage more than one enterprise, and may market their products via a number of channels. Each farmer has his or her own capabilities, knowledge, beliefs, and constraints imposed by climate, natural resources and social and political institutions. Thus farmers are highly diverse and so are the farms that they manage. Furthermore, there are many other important institutions and agricultural decision makers in agriculture, such as suppliers of seed, fertilizer, chemicals and equipment, financiers, and regulatory agencies. Farmers as well as other agricultural institutions thus make complex chains of decisions, and these vary considerably from region to region. An understanding of these institutions and decision chains is needed to know how to tailor climate forecasts for consideration by specific decision makers for specific decisions. These complexities span all scales from farm to globe. Thus, there are many challenges imposed by the extensive, decentralized and diverse nature of agriculture. Because of the biophysical, societal, and institutional complexities of agricultural systems, comprehensive research programs are needed to bridge the gap that now exists between climate forecasts and their routine applications in agriculture (Podestá et al., 1999a).

Part of the challenge of realizing the potential benefits of climate forecasts arises because of our incomplete understanding of the physical and biological effects of climate. Crop response to climate is highly complex and non-linear. Although systems modeling has enabled us to represent and predict much of the response of major field crops to the interactive effects of climate, soil, genotype and management, we will never be able to understand or predict all mechanisms of that response. Indirect effects of climate on insect pests, diseases and weeds are currently difficult to predict. A fairly simple example of an indirect climate effect forced us to defer planned on-farm tests of model-based maize management strategies tailored to ENSO phase. We became aware of problems with simulated response to planting date when preliminary analyses identified optimal planting dates between late May and early June for maize at locations in southern Georgia and Alabama, and northern Florida. However, cooperating farmers indicated that late optimal planting dates predicted by the maize simulation model were unrealistic. Further inquires with agronomists familiar with the region revealed that late-planted maize is susceptible to damage by insect pests that the models do not account for. On-going model development may also be guided by climate-related concerns. During interviews in Florida, fungicide application was frequently mentioned as a potential climate-related management option (Hildebrand et al., 1999). This indicates that the development of a disease module is needed for climate-related decision support.

Further challenges arise from our incomplete understanding of the factors that influence and constrain farmers' decisions. A set of beliefs, knowledge, capabilities, and personal or family goals shape decisions that each farmer makes. Those decisions are constrained by the larger farming system, and the physical, economic, social and political environment. Farmers obtain information and material from a number of sources, and may market their products via a number of channels. The institutions that provide information, supply inputs and serve as marketing channels can either facilitate or constrain farmer decisions. Farmers in the Southeast US have told us that they lack the flexibility to adjust management decisions tailored to climate forecasts. Identifying the reasons for the constraints, and either working around the constraints or finding other opportunities to benefit from climate forecasts will require a concerted effort on the part of both researchers and farmers.

Farmers are well aware of the increasing globalization of agriculture. Interviews in the southeast US and Argentina found high interest among farmers in obtaining predictions of the climate affecting their competition in other regions of the world ((Hildebrand et al., 1999; Royce et al., 2000) trip report, June 1998). At a meeting of grain farmers in Argentina, there was as much interest in the price implications of weather around Chicago as in the production implications of forecasted climate for their region. Likewise, a Florida grower increased his area allocated to Chinese cabbage based on a prediction of adverse climate for California where much of that crop is grown. His results represent a particularly successful example of farm planning based on seasonal climate forecasting. Thus, climate forecasts developed for local use by agricultural decision makers may need to include similar forecasts for other regions of the world.

Some of the challenges associated with the complexity of agriculture become apparent when we consider the prospect of large numbers of farmers adopting management tailored to climate forecasts. For example, the task of supplying agricultural inputs will be quite difficult if demand changes from year to year in response to climate forecasts. Farmers can potentially alter selection and management of crops based on new information obtained within a few weeks or days of planting. Input suppliers, on the other hand, generally need much longer lead times to order and transport chemicals and planting material. Increasing the supply of seed for a particular cultivar generally requires a full growing season. Forecast skill is usually poor at the approximately one-year lead-time that input suppliers would need to adjust supply.

The potential effect of large-scale adoption of flexible management strategies on commodity prices raises additional challenges. A large number of farmers in a region who change crop mix or management in response to a climate forecast could change supply enough to influence prices, particularly for commodities that are traded primarily within the region. Analyses using macroeconomic sector models predict that price effects of widespread use of climate forecasts for agriculture could result in net losses (i.e. negative forecast value) to producers, even though society as a whole would benefit (Mjelde et al., 2000).

5. Conclusions

Simulated results showed a potential value of using climate forecasts for allocating areas of land to different crops averaged from US$ 3 to 5 ha^{-1} for Tifton, a location in the southeastern USA. This was lower than estimates for Pergamino and other locations in the Pampas of Argentina (from US$ 11 to 35 ha^{-1}) for mostly the same crop choices. This result was mainly due to the stronger influences of ENSO on climate in the Pampas during the times of year when summer crops are grown. The potential value of climate forecasts for changing maize management practices, (planting date, hybrid, nitrogen fertilizer amount, and plant density) averaged about US$ 15 ha^{-1} for both locations, about 2% of expected margins. These low percentages reflect both the variability of weather from year to year and the uncertainty of climate forecasts based on ENSO phase alone. By assuming perfect knowledge of daily weather to eliminate all uncertainty associated with climate forecasts, an upper limit of about 25% increase in margins was found at both locations. These results imply that although the value of using ENSO phases to forecast climate via historical data patterns is modest, there is considerable potential for adjusting crop management if climate forecasts can be improved. The complexities of agricultural systems and the uncertainties of climate forecasts suggest that a concerted effort is needed if this technology is to be routinely used in agriculture in the future.

Acknowledgements

This research was partially supported by NOAA-OGP through the Florida Consortium of Universities (University of Florida, Florida State University and University of Miami), by USDA-TSTAR Special Grants Program. Approved for publication by the Florida Agricultural Experiment Station as Publication No. R-07461.

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