An ASAE Meeting Presentation

Paper Number: 053057

Climate Information to Reduce Farm Risk

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**Written for presentation at the
2005 ASAE Annual International Meeting
Sponsored by ASAE
Tampa Convention Center
Tampa, Florida
17 - 20 July 2005**

Abstract. *Predictability of seasonal climate variations associated with ENSO suggest a potential to reduce farm risk by tailoring agricultural management strategies to mitigate the impacts of adverse conditions or to take advantage of favorable conditions. Federal farm policies may enhance or limit the usefulness of this climate information. A representative peanut-cotton-corn non-irrigated north Florida farm was used to estimate the value of the ENSO-based climate information and examine impacts of farm programs under uncertain conditions of climate and prices. Yields from crop model simulations and historical series of prices were used to generate stochastic distributions that were fed into a whole farm model, first, to optimize management practices, and then, to simulate uncertain outcomes under risk aversion, with and without the use of climate information, and with and without the inclusion of farm programs. Results suggest that seasonal climate forecasts have higher value for more risk averse farmers when forecast La Niña or El Niño ENSO phases for offensive responses (taking advantage of favorable conditions). The inclusion of Commodity Loan Programs and Crop Insurance Programs decreased the overall value of the forecast information to even negative levels.*

However, more risk averse farmers could still benefit moderately of El Niño and marginally of La Niña forecasts when they participate of these farm programs.

Keywords. *Farm risk, value of climate information, farm programs, crop insurance, commodity loan program, farm simulation, optimization modeling, Jackson County, Florida, peanut, cotton, maize, corn, policy.*

Introduction

Major improvements in climate predictions related to the phenomenon known as El Niño-Southern Oscillation (ENSO) call for studies to estimate the value of this technology and its potential uses to reduce farm risks. Agricultural sector, among the most vulnerable to climate changes, can use seasonal forecasts to mitigate the impacts of adverse conditions or to take advantage of favorable conditions. However, farm decisions are not isolated and always include decision making institutions such as federal farm policies and regulations that may enhance or limit the usefulness of this climate information (Hansen, 2002).

Several studies have previously estimated the agricultural forecasts value (Letson et al., 2005; Meza et al., 2003; Meza and Wilks, 2003; Hammer et al., 2001), but only few have included the government institutional impacts on the value of the seasonal forecasts (Mjelde et al., 1996, Bosch, 1984). Mjelde et al., 1996 remains the state of the art analysis on how farm programs might influence the value of climate information; but since that time, farm legislation has undergone substantial changes, and researchers have learned a great deal on how to estimate climate information value. An update is required.

Synergies or conflicts between farm programs and climate information represents a critical knowledge gap in how we should think about climate forecast value. Farm programs condition the use of climate information in a variety of ways: a) they limit the range and efficacy of forecast responses since farm programs restrict the crops farmers can grow and how they may grow them; b) farm programs often raise commodity prices, so they also tend to raise land values and enhance trends toward larger farming enterprises; and c) farm programs alter the riskiness of decision environments since they (are intended to) reduce the variability of farming incomes.

The objective of this study is to estimate the impacts of farm programs on the value of ENSO forecasts in a rainfed peanut-cotton-corn farm in Jackson County, Florida. We tested the hypothesis that government interventions might enhance or limit the usefulness of the climate information. This study expands the framework used by Letson et al., 2005 by including the impacts of government farm programs into the estimations of the forecast value. We understand for forecast value as the monetary amount change (i.e., US$ ha-1) in the net income resulting of incorporating seasonal climate forecast information in the farm decision making.

Materials and Methods

1. Representative farm

The study was conducted on a representative 128.7 ha rainfed farm in Jackson County, FL (30.774N, 85.226W) that grows peanut, cotton, and maize in soils type Dothan Loamy Sand. We selected this specific case study because it has similarities in environment (e.g., climate, soils), resources (e.g., farm size, crops growth), and technology (e.g., rainfed agriculture) to other major agricultural production areas in the Southeast United States, which would suggest a broader relevance of our findings.

Jackson has a median annual precipitation of 1466 mm and an average temperature of 19.3 °C (www.AgClimate.org). During the growing season (February-November) the rainfall is 1143 mm and the temperature is 21.7 °C. ENSO phases influence climate in the study area.

2. The Jackson model

We integrated climatic, agronomic, economic, and policy components in a farm decision model. This model first optimizes management practices with and without forecasts and with and without Farm Programs, and then simulates net margins over long periods of time.

The climatic component uses 65 years of daily weather records. The agronomic component stochastically generates crop yields for ENSO phases by re-sampling simulated crop yields of biophysical models. The economic component stochastically generates distributions of likely crop prices based on historical prices and government farm programs.

To test our hypothesis that Federal farm policies may enhance or limit the usefulness of the climate information (Mjelde et al., 1996) we introduced two farm programs consisting of commodity loan programs (CLP) and crop insurances (CIP). The CLP included loan deficiency payments (LDP) and marketing loan benefits (MLB), while the CIP included multi-peril crop insurance (MPCI) and crop revenue coverage (CRC). In the study area, LDP are available for cotton and MLB are available for peanut and maize. Also, MPCI is available for the three crops, but CRC is only available for cotton and maize.

2.1. Agronomic component

2.1.1. Crops yield simulation by ENSO phase

The longest historical daily weather record (including rainfall, T max, T min, and irradiation) representative for Jackson County is 65 years (1939-2003) from the weather station at Chipley (30.783N, 85.483W). During this period of time, 14 years were El Niño and 16 La Niña (Table 1).

Table 1. ENSO phases during the period 1939-2003

El Niño						La Niña					
1941	1952	1958	1964	1966	1970	1939	1943	1945	1950	1955	1956
1973	1977	1983	1987	1988	1992	1957	1965	1968	1971	1972	1974
1998	2003					1976	1989	1999	2000		

These weather series were used to simulate and classify crop yields of peanut, cotton, and maize by ENSO phase. Crops yields were simulated using models in the Decision Support System for Agrotechnology Transfer v4.0 (Jones et al., 2003). We adjusted outcomes from crop model simulations to produce yields with a mean reported by local informants (kg ha-1): 3360 for peanut (J. Marois, Researcher, North Florida Research and Education Center, Quincy, personal communication, October 22, 2004), 730 for cotton, and 6270 for maize (J. Smith, Statistician, North Florida Research and Education Center, Quincy, personal communication, Nov. 23, 2004).

Crop model simulations contemplated contemporary management practices in the region of varieties, fertilization, and planting dates (H.E. Jowers, Co. Extension Director IV, Jackson Co. Extension Office, Marianna; personal communication, Oct. 28, 2004); and representative soil type. For peanut we used the most popular variety in the area, Georgia Green (University of Georgia), a Runner type market variety with medium maturity and moderate resistance to late tomato spotted wilt virus (TSWV) and to cylindricladium black rot (CBR). For cotton, we used a popular medium to full season Delta & Pine Land ® (DP) variety. And for maize we used a common McCurdy 84aa, a medium to full season variety similar to brand name varieties of Monsanto ® (Dekalb) or Pioneer ®.

Nitrogen fertilization was used accordingly to local information, 10 kg at the planting for peanut, 110 kg in 2 applications for cotton, and 135 kg in 3 applications for maize. Peanut was planted between mid-April and mid-June, cotton was planted between mid-April to early-May, and Maize was planted between mid-February and mid-April. Nine planting dates (about one-week apart) were included for peanut and maize and four planting dates were included for cotton.

2.1.2. Generation of synthetic crop yields

Limited duration of daily weather records provided only a few realizations of the ENSO impacts to crop yields (i.e., only 14 El Niño realizations), however a thorough assessment of climate risk and forecast value requires the study of a more complete account of ENSO events. Previous approaches have relied on the use stochastic weather generators to produce synthetic weather (Letson et al., 2005; Meza et al., 2003) and then use this weather data to predict agronomic and economic outcomes. We used a simpler approach consisting of a stochastic yield generator based on simulated crops yields.

Our stochastic yield generator employed re-sampling in three steps. First, A) crop yields simulated by crop models were sorted within an ENSO phase and a planting date. Second, B) a function (logarithmic, exponential, quadratic, or linear; whichever had higher R2) was fit to the data. We used a mathematical function in order to avoid underestimating potential extreme values in the distribution. Third, C) 990 stochastic yields were generated by re-sampling a function. We repeated the procedure for each planting date, of each crop, in each ENSO phase.

2.2. Economic component

2.2.1. Generation of synthetic prices

In order to match our yields, we stochastically generated distributions of 2970 price series for each crop (peanut, cotton, and maize) by simulating a multivariate distribution respecting price covariance among crops based on historical price variability. The procedure followed several steps (for more details see Letson et al., 2005, Appendix B). First, A) we obtained monthly average prices (Jan 1996 – Jan 2005) received by Florida farmers for peanut, cotton, and maize from the USDA National Agricultural Statistical Service (http://www.nass.usda.gov/fl/econ/prices/) and converted them to $ Mg-1 units. B) We studied and graphed the data, estimated their descriptive statistics, and explored their correlation structure. C) We deflated prices to Jan 2005 dollars using the US Consumer Price Index. D) We de-trend the data for seasonal differences by estimating monthly residuals respect to their means. E) We used principal components analysis to decompose the matrix of price residuals into three uncorrelated time series of amplitudes that were separately sampled. F) The sampled values were combined and back transformed to reconstruct crop price residuals. G) We confirmed that the correlation structure of the synthetic price residuals was similar to that of the historical data according to Kolgomorov-Smirnov tests and that the historical price distributions were well reproduced according to quantile-quantile plots. And finally H) we re-introduced seasonal price averages for the harvesting dates of the three crops: Sep 2-Nov 6 for peanut, Sep 22-Dec 28 for Cotton, and Jul 1-Sep 30 for Maize. For the case of cotton, we increased its price by 18.66% to account for the seed value.

2.2.2. Production costs

We consider variable and fixed production costs by crop into the model. Contemporary and local costs of production and labor requirements for the three crops were provided by the North Florida Research and Education Center (J. Smith & T. Hewitt, Enterprises Budgets, Quincy; personal communication, Nov. 23, 2004). The variable (fixed) costs for peanut, cotton, and maize were ($ ha-1) 1080 (344), 1122 (177), and 574 (87), respectively.

2.2.3. Whole farm model

We used a stochastic non-linear whole farm model to study the role of climate forecasts in decision making and to estimate the value of these forecasts. We solved the model to identify optimal decisions and to simulate annual economic outcomes by constraining the model to the optimal settings with and without ENSO information, and with and without Farm Programs.

2.2.3.1. Optimal farm decisions

We sampled 325 years of our synthetic yields and prices to find optimal land allocation decisions, assuming the chance of forecasting a given phase is its historical frequency (14, 35, and 16 for El Niño, neutral, and La Niña phases) for the period 1939-2003. The model selected optimal combinations of 22 possible crop managements for 70 El Niño events, 175 neutral years, 80 La Niña events, and the sum of all of them.

The model maximized the expected utility (U) for one year planning period subject to land and labor availability (Letson et al., 2005), where utility was a power function of wealth based on a constant relative risk aversion R_r (Hardaker et al., 2004), Equations 1 to 4.

$$\max_x E\{U(W_f)\} = \sum_{n=1}^{N}\sum_{i=1}^{3} q_i U(W_0 + \Pi_{i,n})/N \quad (1)$$

$$\sum_{m=1}^{22} X_m = 1; X_m \geq 0 \quad (2)$$

$$\sum_{j=1}^{10} X_m * L_{m,j} \leq \overline{L}_j \quad (3)$$

$$U(W_f) = W_f^{1-R_r}/(1-R_r) \quad (4)$$

where i is the ENSO phases (1=El Niño, 2=neutral, 3=La Niña), j is the month of the labor constraint (1-10, February to November), m is the management alternatives, and n is the years for each optimization (1 to N); Π is income, W_0 and W_f are initial and final wealth, q is the historical likelihood of receiving a given ENSO phase forecast, X is land allocation, and L is labor requirement. This model replicates similar models defined for Letson et al. (2005) and Messina et al. (1999) in Argentina. We constrained the model here to use all land each year to account for realistic crop rotations commonly used in the study area. Local information indicates farmers use different plots of land to rotate these three crops in different years (C.A. Smith, Extension Agent II, Jackson Extension Office, Marianna; personal communication, Nov. 12, 2004); the model does not distinguish among farm fields, but accounts for size of land and management practices on each one of them.

We used the MINOS5 algorithm in GAMS (Gill et al., 2000) along with a randomized procedure to alter starting values and assure global maxima solutions. Every solution identified land allocation for crop enterprises that maximized expected utility for each constant relative risk of aversion (R_r): 0, 0.5, 1, 2, 3, and 4, Hardaker et al. (2004, p. 102).

2.2.3.2. Farm simulation and EVOI calculation

We constrained the farm model to optimal land allocations found by optimizations to simulate net margins for 2970 years (990 for each ENSO phase) using all our synthetic yields and all our synthetic prices. This procedure was repeated for each constant relative risk of aversion.

We estimated the value of the information (EVOI) by comparing the simulated net margins with and without forecast according to their historical proportion frequencies. To be consistent with precedent literature, we estimated EVOI over different planning horizons in certainty equivalent units (US$).

2.3. Introduction of farm programs

Several farm programs exist in place and directly impact agricultural production risk in the United States. Among them, crop insurances, disaster assistance, fixed and countercyclical payments, and commodity loan programs are available for farmers in Jackson County, Florida. In order to evaluate land allocation decisions for our three crops, we were interested in farm programs that depend on actual production and distinguish among commodities as is the case of commodity loan programs and crop insurances.

We were not interested in disaster assistance programs, federal income taxes, and other type of farm program provisions (fixed and countercyclical payments) because they do not depend directly on actual production and farmers have limited or none control of them in their annual decision making. In addition, according to local information (K. Nicodemus, Rural Community Insurance, October 2004) only very few cases can be found for claiming disaster assistance; Federal income taxes have been found to influence only moderately the value of the forecast (Mjelde et al., 1996); and program payments are totally independent of production and farm decision making.

2.3.1. Commodity loan programs

The Federal Agriculture Improvement and Reform Act of 1996 (the 1996 FAIR Farm Act) initiated loan deficiency payments (LDP) programs for several crops, including cotton. The purpose of this LDP program is to provide producers with financial help to market their crops throughout the year. The LDP for a county is determined by comparing the county's loan rate and posted county price (PCP). If the PCP is below the loan rate, then producers are eligible for LDPs. The payment amount is the difference between the loan rate and the PCP (http://www.card.iastate.edu/ag_risk_tools/ldp/). Farm Program of LDP in Jackson County sets a minimum price of $1.14 kg-1 for cotton.

The Farm Security and Rural Investment Act of 2002 (the 2002 FSRIA Farm Act) eliminated the peanut “quota,” but created new forms of farm financial help for peanut growers (http://www.ers.usda.gov/AmberWaves/November04/features/ peanutsector.htm). Among the new sources of government payments is the marketing loan benefit (MLB), which entitles peanut growers to receive marketing assistance loans of $0.39 kg-1 on current production. Also the 2002 FSRIA Farm Act changed the maize MLB to $0.08 kg-1 (http://www.ers.usda.gov/Briefing/Corn/policy.htm). In order to compare EVOI with and without the inclusion of Farm Programs, we applied the LDP to cotton and MLB to peanut and maize in our synthetically generated prices by limiting the minimums to at least the levels of the respective programs. In the case of cotton, we first applied the LDP and then added the value of the seed.

2.3.2. Crop insurance programs

Several crop insurance options are available. To reduce the number of decisions we used the most common insurance products used by Jackson County farmers in 2004 according to the Economic Research Service (www.ers.usda.gov). We used for peanut, multi-peril crop insurance (MPCI) at 70% level; for cotton crop revenue coverage (CRC) at 65% level; and for maize, MPCI at 50% coverage. The MPCI covers yield loss to a level selected, while CRC covers value loss to a selected level (yield multiplied by a price election). The price election selected was the maximum in each one of the cases. It was ($ kg-1) 0.3935, 1.4991, and 0.0964 for peanut, cotton, and maize, respectively. The use of medium levels of yield coverage (peanut and cotton) and highest price coverage is consistent with what producers tend to insure (Mjelde et al., 1996). Insurance premium costs by crop were calculated by multiplying the premium cost by the selected planted area by crop inside the decision function of the model. The local premium costs were ($ ha-1) 69.88, 144.86, and 18.03 for peanut, cotton, and maize, respectively.

An indemnity payment was calculated when the yield (MPCI for peanut and maize) or the value of the yield (CRC for cotton) was lower than the insured threshold in a determined year. The indemnity payment was the amount the farmer would receive in compensation to raise the income of the crop to the insured level. The indemnity payment was added to the income into the objective function by multiplying the land area by the price base and by the amount of loss.

Results and Discussion

1. Optimal land allocation without farm programs

Optimal crop and management choices by ENSO phase are influenced by risk aversion. We present only the case of R_r =1 (Fig. 1). The proportion of crops on the farmland did not change; however there were favorable management practices for different ENSO phases. Later peanut plantings were preferred in El Niño years, while very early cotton plantings were chosen for La Niña phases. Medium to late maize plantings were selected for El Niño and La Niña years, but earlier plantings were selected during neutral years. These crop rotations are consistent with local information. Diversification decreased with risk aversion; e.g., only 2 management alternatives were selected for R_r =4 and only 3 managements alternatives were selected for R_r=0, compared to 4 for R_r =1 when optimized for all years. Crop rotations resulting of the land allocation optimization are consistent with the ranges indicated by local informants. For R_r =0, 0.5, and 1 the proportion of peanut, cotton, and maize were always 35, 36.7, and 28.3%; for R_r=2, 3, and 4 the proportion of the same crops were 0, 37.8, and 62.2%, respectively.

2. Optimal land allocation with farm programs

Application of commodity loan programs (CLP) impacted only marginally in the optimal decisions. For R_r =1, small proportions of planting date crop selection were changed for maize during El Niño years and for cotton during neutral years (Fig. 1 A, B). For R_r =2, 3, and 4 the proportion of peanut, cotton, and maize were 0, 93.6, and 6.4%, respectively.

Application of crop insurance programs (CIP) impacted only moderately the optimal decisions. For R_r =1, small proportions of plating date crop selections were changed for maize during El Niño years, and for peanut and cotton for neutral years (Fig. 1 A, C). For R_r =2, 3, and 4 and neutral years the proportion of peanut, cotton, and maize selection were 0, 93.6, 6.4%, respectively.

The combined impact of CLP and CIP in the optimization of land allocation was also only moderate. For R_r =1, major changes occurred in the planting dates proportions for maize during El Niño years and for cotton and peanut for neutral years. When both programs are present, the proportion of crop selection for R_r =2, 3, and 4 were as in the case of no Farm Programs.

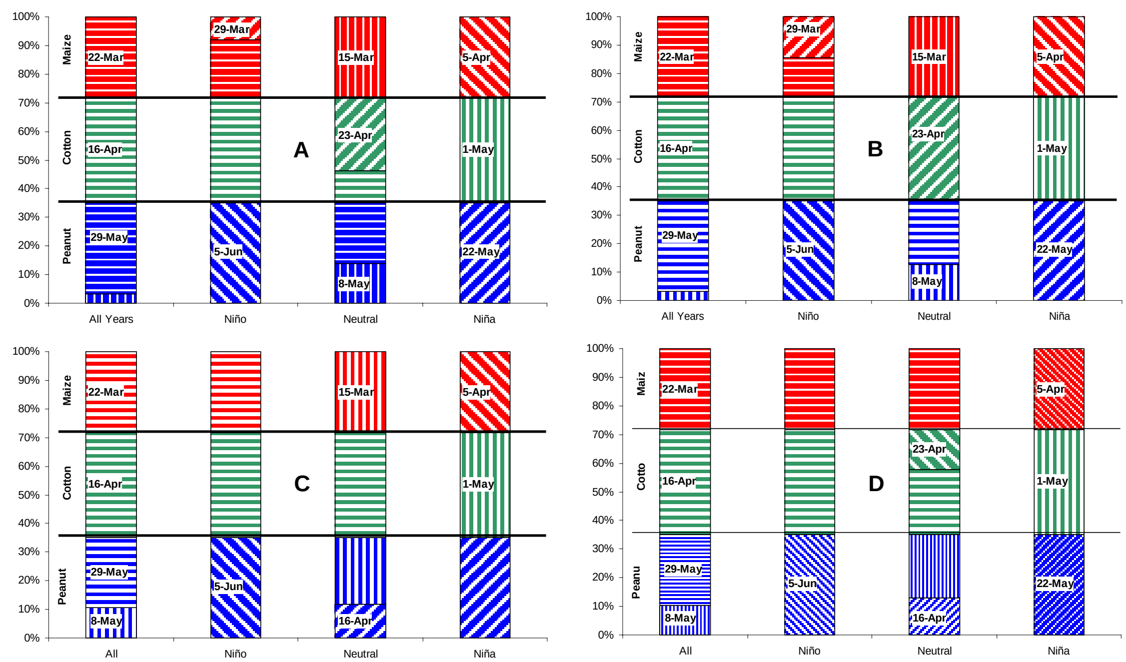

Figure 1. Optimal land allocations (%) when R_r =1. A) Without applying Farm Programs. B) Applying commodity loan programs (CLP). C) Applying crop insurance programs (CIP). D) Applying CLP and CIP.

3. Forecast value without Farm Programs

3.1. Forecast value and risk preferences

We used a single 2970-year interval weighted average of ENSO-phase historical frequency to estimate certainty equivalent (US\$ ha^{-1}) to explore the value of the information (EVOI) and compare it with previous studies. Fig. 2 shows the relationship between ENSO phases, EVOI, and risk aversion levels. Forecast responses in Jackson County combine defensive with offensive risk strategies. Under normal risk aversion (Rr=1), when producers are prepared to minimize income losses (defensively) and to take advantage of favorable conditions (offensively), the average EVOI was \$2.9 ha^{-1}, which increased to \$6.6 ha^{-1} for El Niño events. The value of the information increased considerably to around \$25 ha^{-1} for the average of all years when Rr>1. This was even more valuable for the case of more risk adverse farmers when El Niño or La Niña events were forecast (\$48 ha^{-1}). For less risk averse producers (Rr<1), limited increase in the value of the information was observed for La Niña events and remained steady for El Niño Events (Fig. 2A).

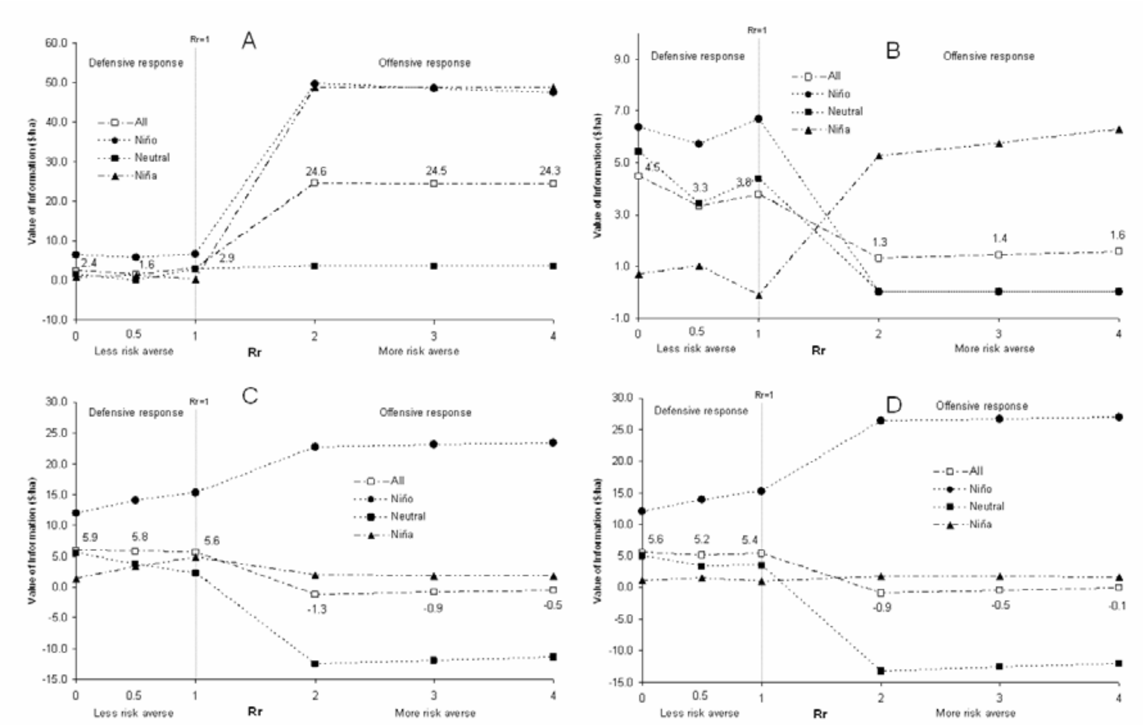

Figure 2. Forecast value by ENSO phase and Rr level. Each EVOI estimated over a single 2970-year interval. EVOI expressed in certainty equivalent units (US\$ ha-1). A) Without applying Farm Programs. B) Applying commodity loan programs (CLP). C) Applying crop insurance programs (CIP). D) Applying CLP and CIP

Following Letson et al. (2005), small-scale Jackson County farmers, like the representative farmer for this study, are risk averse farmers that would use the forecast offensively by being more responsive to La Niña or El Niño events to take advantage of likely favorable conditions. Conversely, large farmers would use the forecast defensively by being more responsive to La Niña phases to avoid losses during these events. For all years, EVOI is \$2.4 ha^{-1} at Rr=0 and it is maximized at \$24.6 ha^{-1} at Rr=2 (similar results were found by Letson et al., 2005, in Pergamino, Argentina). Our findings of EVOI values, which show the best opportunity of forecasts for highly risk averse producers and encourages offensive forecast use, is consistent with previous studies (Letson et al., 2005; Messina et al., 1999; Mjelde et al, 1998; and Katz´s webpage (www.esig.ucar.edu/HP_rick/agriculture.html).

Even a perfect forecast provides a distribution of possible weather outcomes, which will impact crop yields and together with uncertain prices will impact economic returns. A frequency distribution of EVOI estimates is presented in Fig. 3. EVOI range and likelihood are of practical importance because forecast users may want to know the range and likelihood of EVOI as well as the likelihood of negative EVOI estimate. The probability of negative EVOI estimate in Fig. 3

is 831 out of 2970 (28%), which is not negligible. Negative EVOI occurs because of the joint effect of weather and prices.

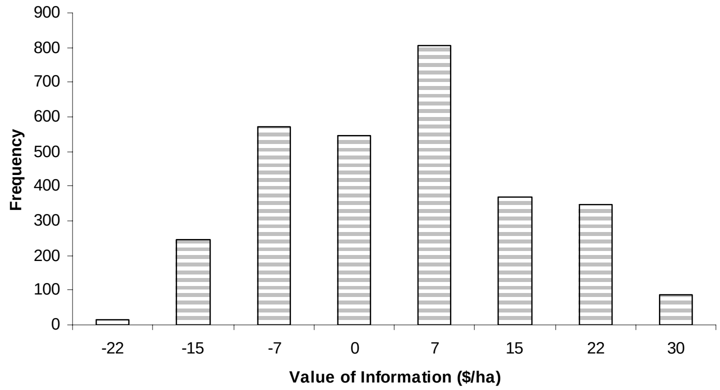

Figure 3. Frequency distribution of EVOI estimates in 100-year horizons for the case of R_r =1. Mean = $4.39 ha^{-1} and 95% confidence interval = $[3.48, 5.30] ha^{-1}

4. Forecast value with Farm Programs

4.1. Forecast value with commodity loan programs

We followed similar analyses to the EVOI estimates when CLP were applied. Fig. 2B shows the relationship between ENSO phases, EVOI and Rr when CLP are included. Overall the value of the information is greatly reduced when CLP are applied. Under normal risk aversion (R_r=1), the average EVOI was slightly higher than not using CLP, $3.8 ha^{-1}, which increased to $6.8 ha^{-1} for El Niño events. This was the highest value of the information. For higher risk averse levels (R_r > 1), the value of the information was substantially lower than when not using CLP, of the order of $1.5 ha^{-1} for average of all years. The EVOI was small but positive for all years; however it was zero for La Niña years and R_r=1 and for El Niño and neutral years and R_r > 1 because there were no differences between the optimal settings when using forecast information.

While for less risk averse farmers (R_r < 1) a defensive response could have slightly better EVOIs than not using CLP, for more risk averse producers (R_r > 1) the value of the information is substantially lower for the case of using CLP. When using CLP, less risk averse farmers (usually large farmers) would slightly benefit with defensive responses during El Niño events, however more risk averse farmers (usually small farmers) would not benefit by using ENSO forecast.

4.2. Forecast value with crop insurance programs

We followed similar analyses to the EVOI estimates when CIP were applied. Fig. 2C shows the relationship between ENSO phases, EVOI and R_r when CIP are included. When CIP is applied, the overall value of the information is greatly reduced to even negative values. However, the EVOI for all years under less or normal risk aversion levels was slightly increased to more than $5.6 ha^{-1}. EVOI was negative ($-0.5 ha^{-1}) for all years and Rr > 2. This was because, EVOI was highly negative (<$-11 ha^{-1}) when neutral years, even when EVOI estimates for El Niño years and were moderately high (>$ 22 ha^{-1}, still under CIP conditions high risk averse farmers could benefit of potential favorable conditions when El Niño years forecast). Over concerned optimal decisions of highly risk averse decision makers create a great difference in the potential gains.

Negative EVOI is possible as reported in previous studies. Negative EVOI occurs because intra-phase variability: e.g., optimization selected a crop combination based on a sample of weather realization and the actual weather occurrence differed in ways that impacted income. Moreover, the incidence of negative EVOI estimates increased when stochastic prices (ENSO independent) are non-favorable for a defined enterprise proposition. Under high risk aversion levels, enterprises with less variable returns are chosen over enterprises with overall higher returns. It was consistent over all optimizations that peanut was not selected for high risk aversion levels even though it was the most profitable enterprise. Also, remember that, we sampled 325 years for our optimization and then constrained the model to the optimal settings. It happened that use of forecast could be a losing proposition when extreme prices and weather interact.

High frequency and overall higher negative values found in this study (including the case of not using farm programs) differ from previous studies. We attempt to explain it based on specific conditions of our Jackson farm system. Jackson County producers are required to use all their land with limited labor available. This fact makes producers select even negative enterprises, in order to use labor as efficiently as possible. For example, cotton was a negative enterprise for all ENSO phases and no farm programs, but it was always selected because it was needed in the natural rotation of crops as described by local informants.

4.3. Forecast value with commodity loan and crop insurance programs

We included both CLP and CIP at the same time and followed similar analyses to the EVOI estimates. Fig. 2D shows the relationship between ENSO phases, EVOI and Rr when CLP and CIP are included. Although the inclusion of both farm programs decreases the overall value of the information, it also buffers the occurrence of negative values as when applied only CIP. The EVOI for all years was negative for Rr >1 varying between \$-0.1 and \$-0.9 ha^{-1}. The value of the information was positive, but marginal for La Niña years and for Rr >1. It was always positive for El Niño years and it had moderate values (\$ 26 ha^{-1}) for Rr >1, indicating that highly risk averse farmers would still benefit of using offensively El Niño forecast by taking advantage of potential advantageous situations when CLP and CIP are in place.

Conclusions

Forecast value is inherently probabilistic even for perfect ENSO phase forecast and must be estimated and communicated as dispersion rather than a single point estimate. Our numerous synthetic prices and yields allowed us to generate probabilistic distributions of the value of the forecasts. Each estimate we report is associated with its probability of occurrence. Within these distributions, negative value of the forecast information exists and is not negligible (Letson et al., 2005).

As hypothesized, farm programs substantially impact the value of forecasts. Farm programs as commodity loan programs and crop insurance programs reduce farm income variability and the riskiness of the farm enterprises. Consequently, the inclusion of CLP and CIP tend to reduce the overall value of the climate information and increase the likelihood of negative values of the information. However, depending upon the risk aversion level of the farmer it could vary considerably. Decision making institutions and regulations such as farm programs will always affect farm riskiness and farmers' decisions. They should be included in the analyses of decisions.

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