FARM PROGRAMS EFFECTS ON THE VALUE OF SEASONAL CLIMATE INFORMATION[1]

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ABSTRACT

Predictability of seasonal climate variations associated with ENSO suggests 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 and risk aversion levels. 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 La Niña or El Niño ENSO phases are forecast. Highly risk-averse farmers could benefit from the forecast by taking advantage of potential favorable conditions (offensive responses). The inclusion of Commodity Loan Programs (CLP) and Crop Insurance Programs (CIP) decreased the overall value of the forecast information even to negative levels. However, more risk-averse farmers could still benefit moderately from El Niño and marginally from La Niña forecasts when they participate in CLP and CIP.

Key words: farm risk reduction, farm government intervention, El Niño Southern Oscillation (ENSO), whole farm simulation, forecast value.

INTRODUCTION

Major improvements in climate predictions based on El Niño-Southern Oscillation (ENSO) phenomena call for studies to estimate the value of this technology and its potential uses to reduce farm risks (Phillips et al., 2002; Podestá et al., 2002). The 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 (Bert et al., *in press*; Chen et al., 2002; Jagtap et al., 2002). However, farm decisions do not occur in isolation and may be

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influenced by decision making institutions such as federal farm policies and regulations that enhance or limit the usefulness of climate information (Hansen, 2002).

Several studies have estimated the value of agricultural forecasts (Hammer et al., 2001; Letson et al., 2005; Meza and Wilks, 2003), but few have included the impacts of government institutions on the value of the seasonal forecasts (Bosch, 1984; Mjelde and Hill, 1999; Mjelde et al., 1996). Mjelde et al. (1996) remains the state of the art analysis on how farm programs might influence the value of climate information; but since this analysis was conducted farm legislation has undergone substantial changes and researchers have learned much more about how to apply climate information and how to estimate the value of climate information. The use of biophysical crop simulation models together with stochastic weather generators to characterize ENSO intra-phase variations and confidence intervals have played a major role in the study of the value of the climate information in recent years.

Synergies and conflicts between farm programs and climate information represent critical knowledge gaps in how we think about climate forecast value. Farm programs condition the use of climate information in at least two ways:

- they may limit the range and efficacy of forecast responses if farm programs restrict the crops farmers can grow and how they may grow them;
- farm programs may alter the riskiness of decision environments because they are intended to reduce the year-to-year variability of a farm income

The objective of this study was to estimate the impacts of USDA farm programs on the value of ENSO-based 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.

MATERIALS AND METHODS

Representative farm

The study was conducted on a representative 129-ha rainfed farm in Jackson County, FL (30.774N, 85.226W) that grows peanut, cotton, and maize in soil type *Dothan loamy sand.* We selected this specific case study because it has similar environment (e.g., climate, soils), resources (e.g., farm size, crops grown), and technology (e.g., rainfed agriculture) to other major agricultural production areas in the southeastern United States, which would suggest a broader relevance of our findings.

Jackson County 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 precipitation and temperature in Jackson County during the growing season, but not in a consistent manner. For example, higher total rainfall amounts are expected during El Niño events; however probability of rainfall April, May, and October is greater during La Niña events.

The 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 each ENSO phase by re-sampling simulated crop yields produced by 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 USDA Federal farm policies may enhance or limit the usefulness of the climate information (Mjelde et al., 1996) we introduced two farm programs, a Commodity Loan Program (CLP) and Crop Insurance Program (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, LDPs are available for cotton and MLBs are available for peanut and maize. Also, MPCI is available for all three crops, but CRC is available only for cotton and maize.

2.2.1. Agronomic component

2.2.1.1. 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 were La Niña (Table 1).

-Table 1-

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 align yields with means reported by local informants: 3360 kg ha^{-1}for peanut (J. Marois, Researcher, North Florida Research and Education Center, Quincy, personal communication, October 22, 2004), 730 kg ha^{-1} for cotton, and 6270 kg ha^{-1}for maize (J. Smith, Statistician, North Florida Research and Education Center, Quincy, personal communication, Nov. 23, 2004). Crop simulations were ran using contemporary management practices in the region for varieties, fertilization, and planting dates (H.E. Jowers, Co. Extension Director IV, Jackson Co. Extension Office, Marianna; personal communication, Oct. 28, 2004); and the representative soil type *Dothan loamy sand*. 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. For maize we used McCurdy 84aa, a medium- to full-season variety similar to brand name varieties of Monsanto ® (Dekalb) or Pioneer ®.

Nitrogen fertilization was applied according to local extension recommendations, namely, 10 kg at planting for peanut, 110 kg in 2 applications for cotton, and 135 kg in 3 applications for maize. Maize was planted between mid-February and mid-April, cotton was planted between mid-April and early-May, and peanut was planted between mid-April and mid-June (Table 2). Nine planting dates (about one-week apart) were simulated for peanut and maize and four planting dates were simulated for cotton.

2.2.1.2. Generation of synthetic crop yields

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

Our stochastic yield generator employed re-sampling in three steps.

1. Sort simulated crop yields simulated by ENSO phase and a planting date.
2. Calculate the best fitting function (logarithmic, exponential, quadratic, or linear; whichever had a higher R^2) for the data. We used a mathematical function in order to avoid underestimating potential extreme values in the distribution.
3. Generate 990 stochastic yields by re-sampling the best fitting function.

We repeated the procedure for each planting date, each crop, and each ENSO phase. Table 2 shows mean and standard deviation of synthetically generated crop yields across ENSO phases and planting dates.

-Table 2-

2.2.2. Economic component

2.2.2.1. 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).

1. 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.
2. Study and graph the data, estimate their descriptive statistics, and explore their correlation structure.
3 Deflated prices to Jan 2005 dollars using the US Consumer Price Index.
4. De-trend the data for seasonal differences by estimating monthly residuals with respect to their means.

5. Use principal component analysis to decompose the matrix of price residuals into three uncorrelated time series of amplitudes that were separately sampled.
6. Combine sampled values combined and back transform them to reconstruct crop price residuals.
7. Confirm 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.
8, Re-introduce 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.

Distributions for the synthetically generated prices can be seen in Fig. 1. Note that the price distributions are not historical values, but are distributions consistent with historical variability.

In order to study the impacts of potential future peanut price reductions in our value of information portfolio, we created an scenario of arbitrarily reducing the price of peanut by 33% and estimated the value of the information under those conditions.

2.2.2.2. Production costs

We consider variable and fixed production costs by crop in the model. Contemporary 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 (\$ ha^{-1}) were: 1080 (344) for peanut, 1122 (177) for cotton, and 574 (87) for maize.

2.2.2.3. 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 whole farm 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.

2.2.2.3.1. 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 El Niño, 35 neutral, and 16 La Niña phases) for the period 1939-2003. The model selected optimal combinations of 22 possible crop management practices (Table 2) 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 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.

$$\max_x E\{U(W_f)\} = \sum_{n=1}^{N}\sum_{i=1}^{3} q_i U(W_0 + \prod_{i,n}) / N \qquad \text{[Eq. 1]}$$

$$\sum_{m=1}^{22} X_m = 1; X_m \geq 0 \qquad \text{[Eq. 2]}$$

$$\sum_{j=1}^{10} X_m * L_{m,j} \leq \overline{L}_j \qquad \text{[Eq. 3]}$$

$$U(W_f) = W_f^{1-R_r} / (1 - R_r) \qquad \text{[Eq. 4]}$$

Where:
- i = ENSO phase (1=El Niño, 2=neutral, 3=La Niña),
- j = month of the labor constraint (1-10, February to November),
- m = management alternative from Table 2,
- n = year for each optimization (1 to N);
- $\prod$ = income (US\$ yr^{-1}),
- W_0 = initial wealth (US\$ yr^{-1}),
- W_f = final wealth (US\$ yr^{-1}),
- q = historical likelihood of an ENSO phase forecast (%),
- X = land allocation (ha),
- L = labor requirement (day).

This model replicates similar models defined by Letson et al. (2005) and Messina et al. (1999) for Argentina. We constrained the model 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 land area 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).

2.2.2.3.2. Farm simulation and Estimate of the Value of the Information (EVOI)

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

We define forecast value (EVOI) as the monetary amount of change in the net income resulting from incorporating seasonal climate forecast information and risk aversion levels in farm decision making.

We estimated 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 and directly impact agricultural production risk in the United States. Among them, crop insurance, 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 either do not depend directly on actual production or farmers have limited or no control over them in their annual decision making. In addition, very few cases can be found for farmers in Jackson County that claimed disaster assistance (K. Nicodemus, Rural Community Insurance, October 2004); also, 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 payment (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/). The USDA Farm Program in Jackson County sets a minimum price of $1.14 kg^{-1} for cotton LDPs.

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 minima 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. Distribution of generated synthetic prices before and after the inclusion of programs are presented in Fig. 1.

-Figure 1-

2.3.2. Crop insurance programs

Several crop insurance options are available. To limit possible decisions to a logistically manageable number we used the most common insurance products used by Jackson County farmers in 2004 according to the Economic Research Service (www.ers.usda.gov). For peanut we used multi-peril crop insurance (MPCI) at the 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 selected level, while CRC covers loss value 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 for peanut, 1.4991 for cotton, and 0.0964 for maize. The use of average levels for 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 to the farmer were ($ ha^{-1}): 29.16 for peanut, 50.16 for cotton, and 7.66 for maize.

An indemnity payment was calculated when yield (MPCI for peanut and maize) or crop value (CRC for cotton) was less 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 in the objective function by multiplying the land area by the price base and by the amount of loss.

RESULTS AND DISCUSSION

3.1. 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. 2). The proportion of crops on the farm did not change. However, there were favorable management practices for different ENSO phases that maximized the farm net income. 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. 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 and land allocation from optimizations are consistent with the ranges indicated by local informants. For R_r =0, 0.5, and 1 the proportion was 35% of peanut, 36.7% cotton, and 28.3% maize; for R_r =2, 3, and 4 the proportion was 0% of peanut, 37.8% of cotton, and 62.2% of maize.

3.2. Optimal land allocation with farm programs

3.2.1. Optimal land allocation with Commodity Loan Programs

Application of CLP only marginally affected 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. 2 A, B). For R_r =2, 3, and 4 the proportion was 0% of peanut, 93.6% of cotton, and 6.4% of maize.

-Figure 2-

3.2.2. Optimal land allocation with Crop Insurance

Application of CIP only moderately affected 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. 2 A, C). For R_r =2, 3, and 4 the proportion was 0% of peanut, 37.8% of cotton, and 62.2% of maize, with variants in the planting dates.

3.2.3. Optimal land allocation with Commodity Loan and Crop Insurance Programs

The combined impact of CLP and CIP on the optimization of land allocation was also only moderate. For R_r =1, major changes occurred in the planting dates and 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.

3.2. Forecast value without farm programs

3.2.1. Forecast value and risk preferences

We used a single 2970-year interval weighted average of ENSO-phase historical frequency to estimate certainty equivalent to explore and to compare the value of the information (EVOI) with previous studies. Fig. 3 shows the relationship between ENSO phases, EVOI, and R_r . Risk tolerant farmers employ a defensive response, while risk averse farmers use forecasts defensively. Forecast responses in Jackson County combine defensive with offensive risk strategies. Under normal risk aversion (R_r =1), when producers are prepared to minimize income losses (defensively) and to take advantage of favorable conditions (offensively), the average EVOI was \$2.90 ha^{-1}, which increased to \$6.60 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 $R_r > 1$. 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 or risk tolerant producers ($R_r < 1$), limited increase in the value of the information was observed for La Niña events and remained steady for El Niño Events (Fig. 3A).

Small-scale Jackson County farmers, like the representative farmer for this study, are typically 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 \$2.40 ha^{-1} at R_r =0 and it is maximized at \$24.60 ha^{-1} at R_r =2. Similar results were found by Letson et al. (2005) in Pergamino, Argentina.

-Figure 3-

Our findings of EVOI, which show the best opportunity of application of seasonal climate forecasts by highly risk averse producers and encourages offensive forecast use, is consistent with previous studies (Letson et al., 2005, 2001; 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 affect crop yields and, with uncertain prices, will affect economic returns. A frequency distribution of EVOI estimates is presented in Fig. 4.

-Figure 4-

EVOI range and probability 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 estimates. The probability of negative EVOI estimates in Fig. 4 is 831 out of 2970 (28%), which is not negligible. Negative EVOI occurs because of the joint effect of weather and prices.

Prices of peanut are still distorted by government regulations. Even after the 2002 Farm Act that abolished the peanut quota, there are still quota buyout, base acreage, and other peanut price programs. These peanut price incentives are likely to disappear in the near future. Consequently, it is highly likely that the final prices received by peanut farmers will continue to decrease in the near future. The Economic Research Service, ERS, (http://www.ers.usda.gov) estimates this reduction on the order of 33% of current likely prices. Also, statistics and projections from ERS indicate that peanut exports from the US will remain marginal and not have major impacts on the domestic peanut prices.

The results of peanut price reductions in our value of information portfolio, by arbitrarily reducing the price of peanut by 33% indicated that there were no substantial changes in the

EVOI estimates. For example, compared with the original case, the average EVOI when the price of peanut was 33% lower only decreased \$0.20 ha^{-1} under risk normality (R_r =1), and it only decreased around \$2.40 ha^{-1} for the average of all years when $R_r > 1$. The curves when using 33% lower peanut prices were very similar to Figure 3A.

3.3. Forecast value with farm programs

3.3.1. Forecast value with commodity loan programs

We followed similar analyses to the EVOI estimates when CLPs were applied. Fig. 3B shows the relationship between ENSO phases, EVOI and R_r when CLPs are included. Overall, the value of the information is greatly reduced when CLPs are applied. Under normal risk aversion (R_r =1), average EVOI was slightly higher than when not using CLP, \$3.80 ha^{-1}, which increased to \$6.80 ha^{-1} for El Niño events. EVOI for El Niño was the highest value of the information when including CLPs. For more risk averse farmers ($R_r > 1$), the value of the information was substantially lower than when not using CLP, on the order of \$1.50 ha^{-1} for the average of all years. The EVOI was small but positive for all years. The EVOI was zero for La Niña years and $R_r = 1$ as well as for El Niño and neutral years and $R_r > 1$ because there were no differences between the optimal settings when using forecast information.

Whereas for less risk averse or risk tolerant 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-scale 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.

3.3.2. Forecast value with crop insurance programs

We followed similar analyses to the EVOI estimates when CIPs were applied. Fig. 3C shows the relationship between ENSO phases, EVOI and R_r when CIPs 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 \$5.60 ha^{-1}. EVOI was negative (\$-0.50 ha^{-1}) for all years and $R_r > 2$. Negative EVOI for all years for $R_r > 2$ occurred because EVOI was highly negative (<\$-11 ha^{-1}) when neutral years, even when EVOI estimates for El Niño years were moderately high (>\$ 22 ha^{-1}). Still under CIP conditions highly risk averse farmers could benefit by potential favorable conditions when El Niño years are 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 (Letson et al., 2005; Mjelde et al., 1996). Negative EVOI occurs because of intra-phase variability: e.g., optimization selected a crop combination based on a sample of weather realizations and the actual weather occurrence differed in ways that impacted income. Moreover, the incidence of negative EVOI estimates increased when stochastic prices, which are ENSO independent, are unfavorable for a defined enterprise proposition. Under high risk aversion levels, enterprises with returns that have smaller variability are chosen over enterprises with overall higher returns. For all optimizations, peanut was not selected for high risk aversion levels even though it was the most profitable enterprise. In addition, high frequency of negative EVOI may be a consequence of constraining the model to optimal settings obtained from the sampled 325 years. Use of a seasonal climate forecast could result in negative EVOI when extreme price fluctuations and extreme weather conditions coincide. High frequency and overall higher negative values found in this study, including the case of not using farm programs, differ from previous studies. In our model, 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.

3.3.3. 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. 3D shows the relationship between ENSO phases, EVOI and R_r when CLP and CIP are included. Although the inclusion of both farm programs decreases the overall value of a seasonal climate forecast, it also buffers the occurrence of negative values as when is only CIP applied. The EVOI for all years is negative for $R_r > 1$ varying between \$-0.10 ha^{-1} and \$-0.90 ha^{-1}. The value of the information was positive, but marginal for La Niña years and for $R_r > 1$. It was always positive for El Niño years and it had moderate values (\$ 26 ha^{-1}) for $R_r > 1$, indicating that highly risk averse farmers would still benefit by using El Niño forecast offensively by taking advantage of potential advantageous situations when CLP and CIP are in place.

4. Conclusions

As hypothesized, farm programs substantially affect the potential value of seasonal climate forecasts. Farm programs such 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 tends to reduce the overall value of the climate information and increase the likelihood of negative values of information. However, depending upon the risk aversion level of the farmer, the value of the information 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.

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).

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