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The value of climate information when farm programs matter

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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, 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 crop selection and planting dates, 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

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moderately from El Niño and marginally from La Niña forecasts when they participate in CLP and CIP.

Keywords: Farm risk reduction; Farm government intervention; El Niño Southern Oscillation; Whole farm simulation; Forecast value

1. 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 (Podestá et al., 2002; Phillips 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., 2006; Jagtap et al., 2002; Chen et al., 2002). However, farm decisions do not occur in isolation and may be influenced by 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 value of agricultural forecasts (Letson et al., 2005; Meza and Wilks, 2003; Hammer et al., 2001), but only a few have included the impacts of government institutions on the value of the seasonal forecasts (Mjelde and Hill, 1999; 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 much about 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 recent years.

Synergies or conflicts between farm programs and climate information represent 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. They limit the range and efficacy of forecast responses since farm programs may restrict the crops farmers can grow and how they may grow them. In addition, 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 define forecast value or risk adjusted net income as the monetary amount of change (i.e., US$ ha^{-1}) in the net income resulting from incorporating seasonal climate forecast information and risk aversion levels in farm decision making.

2. Materials and methods

2.1. Location and climatic characteristics

The study was conducted on a representative 130 ha rainfed farm in Jackson County, FL that grows peanut, cotton, and maize in soil 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 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.

El Niño Southern Oscillation or ENSO is a phenomenon characterized by changes in the sea surface temperature of the equatorial Pacific Ocean that affects the atmosphere and cause seasonal climate variations around the globe (Ropelewski and Halpert, 1986). In Florida, rainfall is highly sensitive to ENSO phases with an average excess of about 40% of the normal rainfall across most of the state during an El Nino year, with deficits of about 30% lasting during a La Nina year (Jagtap et al., 2002). Florida also has average temperatures 1–2 °C below normal during El Nino years, whereas La Nina brings temperatures 1–2 °C above normal during winter months (Jagtap et al., 2002). Hansen et al. (1998a,b, 1999) and Mavromatis et al. (2002) have found that ENSO influenced yields of most of the crops in Florida.

The weather station at Chipley (30.783N, 85.483W) was used as representative for Jackson Co., which presented 1143 mm of rainfall and 21.7 °C of mean temperature during the growing season (February–November). ENSO phases influence precipitation and to a lesser extent temperature in Jackson Co. In general, higher precipitation levels and lower temperatures are observed during El Niño years, especially before planting. During La Niña years, the opposite is observed (Fig. 1).

2.2. The Jackson climate risk assessment model

We integrated climatic, agronomic, economic, and policy components (Fig. 2) 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.

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 Insurance Programs (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.

2.2.1. 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

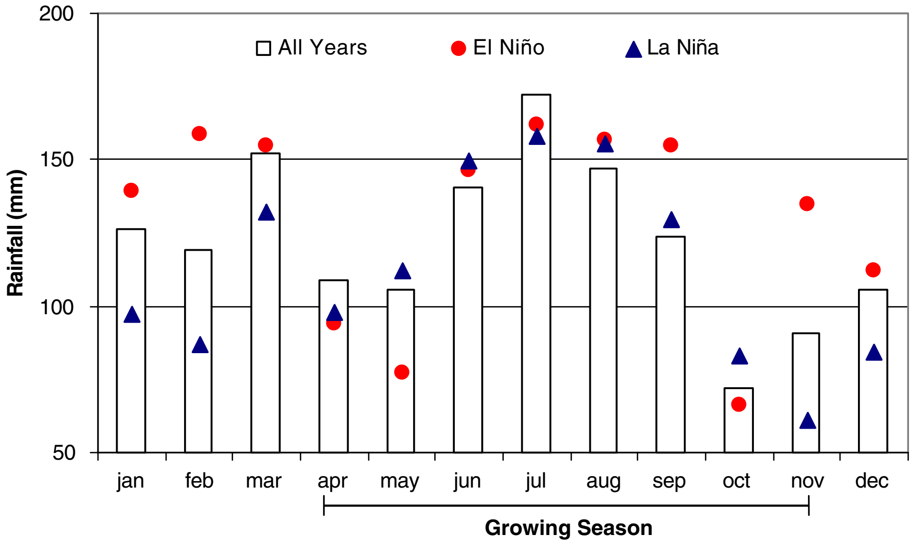

Fig. 1. Historical (1950–2004) monthly rainfall in Jackson County, FL for El Niño and La Niña ENSO phases with respect to all years. *Source*: www.AgClimate.org.

County is 65 years (1939–2003) from the weather station at Chipley. During this period of time, 14 years were El Niño and 16 La Niña (Table 1) as defined by Mavromatis et al. (2002). For detailed climate information used in this study, please refer to www.AgClimate.org.

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, 22 October, 2004), 730 for cotton, and 6270 for maize (J. Smith, Statistician, North Florida Research and Education Center, Quincy, personal communication, 23 November, 2004). Crop model simulations contemplated 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, 28 October, 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. 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®.

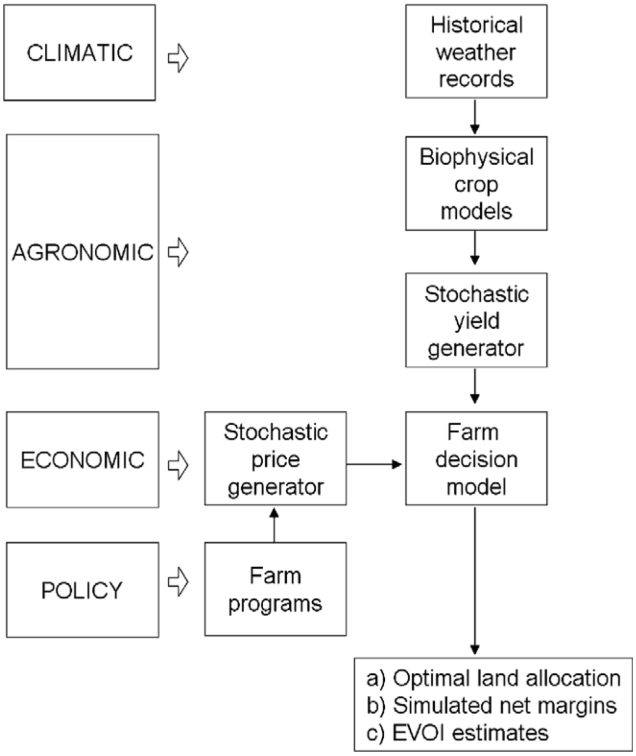

Fig. 2. Simulation framework. Climatic, agronomic, economic, and policy components of the Jackson model (adapted from Letson et al. (2005), pg. 168). *Note*: EVOI is the estimated value of the information.

Table 1
ENSO phases during the period 1939–2003

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

Nitrogen fertilization was used according to local information, 10 kg at planting for peanut, 110 kg in two 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 (Table 2). Nine planting dates (about one-week apart) were included for peanut and maize, and four planting dates were included for cotton.

Table 2
Crops, varieties, planting dates and synthetic yields

Crop/variety	Code	Planting date	Synthetic yields (kg ha^{-1})							
			All years		El Niño		Neutral		La Niña	
			Mean	STD	Mean	STD	Mean	STD	Mean	STD
Peanut/Georgia Green	m1	16 April	3078	1275	2918	1308	3261	1507	3055	916
	m2	23 April	3150	1276	3077	1339	3151	1471	3221	961
	m3	1 May	3217	1272	3150	1232	3202	1474	3298	1076
	m4	8 May	3332	1318	3303	1235	3338	1430	3356	1282
	m5	15 May	3360	1225	3313	1146	3278	1257	3489	1260
	m6	22 May	3361	1210	3390	1064	3352	1248	3341	1305
	m7	29 May	3373	1266	3402	1224	3371	1201	3346	1368
	m8	5 June	3341	1327	3440	1389	3288	1238	3296	1344
	m9	12 June	2956	1477	3008	1613	2982	1376	2877	1429
Cotton/Delta & Pine Land	m10	16 April	720	78	720	78	729	84	711	69
	m11	23 April	717	81	707	79	736	80	709	81
	m12	1 May	714	84	699	89	733	70	711	89
	m13	8 May	715	76	696	60	727	72	722	89
Maize/ McCurdy 84aa	m14	15 February	5253	1708	4437	1190	5671	2040	5651	1475
	m15	22 February	5953	2097	5767	2078	5869	2218	6223	1963
	m16	1 March	5877	2099	5698	2162	6316	1685	5618	2327
	m17	8 March	6163	2109	5836	2280	6787	2125	5864	1745
	m18	15 March	6471	2085	6043	2427	6836	1966	6534	1727
	m19	22 March	6454	1988	6168	2294	6704	1894	6489	1692
	m20	29 March	6510	1874	6181	2228	6582	1657	6768	1630
	m21	5 April	6138	1893	5505	2013	6280	1731	6628	1745
	m22	12 April	5379	1687	4658	1184	5789	1745	5690	1818

We selected this limited set of decisions consistent of crops and planting dates inside our modeling framework in order to not over complicate the problem to be solved and to have parsimony and clarity in our results.

2.2.1.2. 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 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. First, crop yields simulated by crop models were sorted for an ENSO phase and a planting date. Second, a function (logarithmic, exponential, quadratic, or linear; whichever had a higher R^2) was fit to the data. We used a mathematical function in order to avoid underestimating potential extreme values in the distribution. Third, 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.

Our simulated yields are consistent with previous research and data in Florida. These are supported by Hansen et al. (1998a) findings, in which historical data in La Niña years showed greater maize yields with lower deviations compared with lower yields and greater deviations during El Niño years. Likewise, our peanut yields are consistent with Mavromatis et al. (2002) who found greater yields during La Niña years and Fraisse et al. (2005) who predicted between 10 and 20% higher probabilities to collect yield indemnity payment during El Niño years than during La Niña years due to lower yields. In addition, results from Fraisse et al. (2005) pointed out greater peanut yields for medium to late plantings as in our simulated yields. For the case of cotton yields, Hansen et al. (1998a) did not found significant differences among ENSO phases, but historical data indicate a trend of greater yields during El Niño years as it has been found in our simulation.

Table 2 shows mean and standard deviation of synthetically generated crop yields across ENSO phases and planting dates.

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). First, we obtained monthly average prices (January 1996–January 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/). We estimated their descriptive statistics, and explored their correlation structure. We deflated prices to Jan 2005 dollars using the US Consumer Price Index. We de-trended the data for seasonal differences by estimating monthly residuals with respect to their means. We used principal component analysis to decompose the matrix of price residuals into three uncorrelated time series of amplitudes that were separately sampled. The sampled values were combined and back transformed to reconstruct crop price residuals. 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, we re-introduced seasonal price averages for the harvesting dates of the three crops: 2 September–6 November for peanut, 22 September–28 December for Cotton, and 1 July–30 September for Maize. For the case of cotton, we increased its price by 18.66% to account for the seed value. We stress the price distributions are not historical values, but distributions consistent with historical variability.

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, 23 November 2004).

The variable costs ($\$\ \text{ha}^{-1}$) were 1088 for peanut, 1122 for cotton, and 574 for maize. The fixed costs ($\$\ \text{ha}^{-1}$) were 344 for peanut, 177 for cotton, and 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 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 to the three crops and planting date 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 decisions 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), Eqs. (1)–(3), (5):

$$\max_{x} E\{U(W_f)\} = \sum_{n=1}^{N}\sum_{i=1}^{3} q_i U\left(W_0 + \prod_{i,n}\right)\Big/ N \tag{1}$$

$$\sum_{m=1}^{22} X_m = 1; X_m \geqslant 0 \tag{2}$$

$$\sum_{j=1}^{10} X_m^* L_{m,j} \leqslant \overline{L}_j \tag{3}$$

$$\prod = \sum_{m=1}^{22} X_m Y_m P_m - C_m \tag{4}$$

$$U(W_f) = W_f^{1-R_r}/(1-R_r) \tag{5}$$

where i is the ENSO phase (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 alternative of Table 2, and n is the year for each optimization ($1 - N$); $\prod$ 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 the labor requirement. Y is yield, P is price, and C is production cost. This model replicates similar models defined by Letson et al. (2005) and Messina et al. (1999) for 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, 12 November 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).

2.2.2.3.2. Farm simulation and EVOI calculation. We constrained the farm model to optimal land allocations 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 expected 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 the 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 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 insurance.

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, 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 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 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. The value of the seed is unaffected by the farm programs. Distribution of generated synthetic prices before and after the inclusion of programs can be seen in Fig. 3.

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). 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

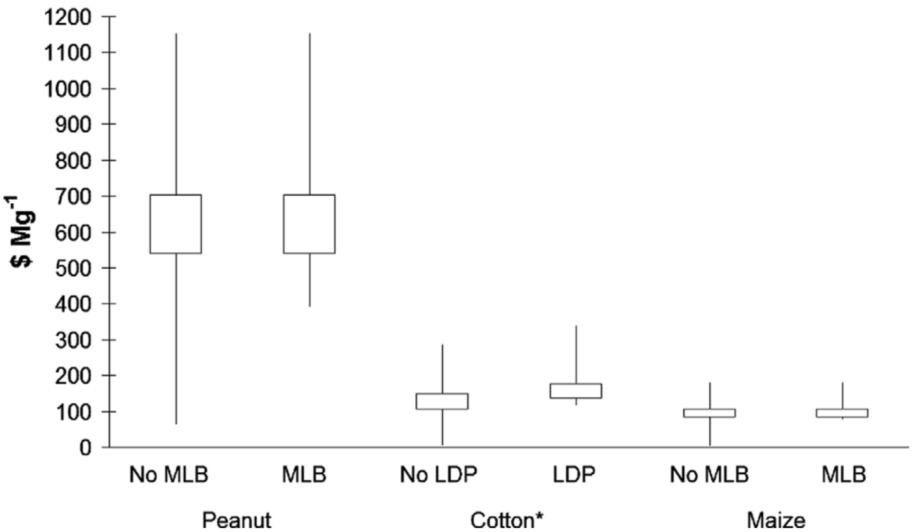

Fig. 3. Synthetic price distributions with and without farm programs. $N = 2970$. Maximum, 75th percentile, 25th percentile, and minimum for each box plot. MLB is marketing loan benefit. LDP is loan deficiency payment. *Price of cotton is \$100 kg^{-1} units and includes the value of the seeds.

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, 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 to the farmer were ($\$ ha^{-1}$) 29.16, 50.16, and 7.66 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 in the objective function by multiplying the land area by the price base and by the amount of loss.

3. Results and discussion

3.1. Optimal land allocation and planting date without farm programs

Optimal crop and management choices by ENSO phase are influenced by risk aversion. The proportion of crops on the farm did not change by ENSO phase for the case of $R_r = 1$ (Table 3). However, there were favorable planting dates 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. Diversification decreased with risk aversion; e.g., only 2 crop planting dates were selected for $R_r = 4$ and only 3 crop planting dates 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 of peanut, cotton, and maize was always 35%, 36.7%, and 28.3%; for $R_r = 2$, 3, and 4 the proportion of the same crops was 0%, 37.8%, and 62.2%, respectively, with no peanut being produced.

3.2. Optimal land allocation and planting date with farm programs

3.2.1. Optimal land allocation and planting date with Commodity Loan Programs

Application of 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 (Table 3). For $R_r = 2$, 3, and 4 the proportion of peanut, cotton, and maize were 0%, 93.6%, and 6.4%, respectively.

Table 3
Optimal land allocation (%) 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			
		All Years (%)	Niño (%)	Neutral (%)	Nina (%)	All Years (%)	Niño (%)	Neutral (%)	Nina (%)	All Years (%)	Niño (%)	Neutral (%)	Nina (%)	All Years (%)	Niño (%)	Neutral (%)	Nina (%)
Peanut	16 April											12	35			13	
	23 April																
	1 May																
	8 May	3		14		3		13		11		23		10		22	
	15 May																
	22 May				35				35								35
	29 May	32		21		32		22		25				25			
	5 June		35				35				35				35		
	12 June																
Cotton	16 April	37	37	11		37	37			37	37	37		37	37	23	
	23 April			25				37								14	
	1 May				37				37				37				37
	8 May																
Maize	15 February																
	22 February																
	1 March																
	8 March			28				28									
	15 March											28					
	22 March	28	20			28	14			28	28			28	28	28	
	29 March		8				14										
	5 April				28				28				28				28
	12 April																

3.2.2. Optimal land allocation and planting date with Crop Insurance

Application of CIP impacted only moderately the optimal decisions. For $R_r = 1$, small proportions of planting date crop selections were changed for maize during El Niño years, and for peanut and cotton for neutral years (Table 3). For $R_r = 2$, 3, and 4 the proportion of peanut, cotton, and maize selection were 0%, 37.8%, and 62.2%, respectively, with variants in the planting dates.

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

The combined impact of CLP and CIP in the optimization of land allocation was also only moderate. For $R_r = 1$, only changes occurred in the planting dates and proportions for maize during El Niño years and for cotton and peanut for neutral years (Table 3). 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.

3.3. Forecast value without farm programs

3.3.1. 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 expected value of the information (EVOI) and compare it with previous studies. Fig. 4 shows the relationship between ENSO phases, EVOI, and R_r. Risk tolerant farmers employ

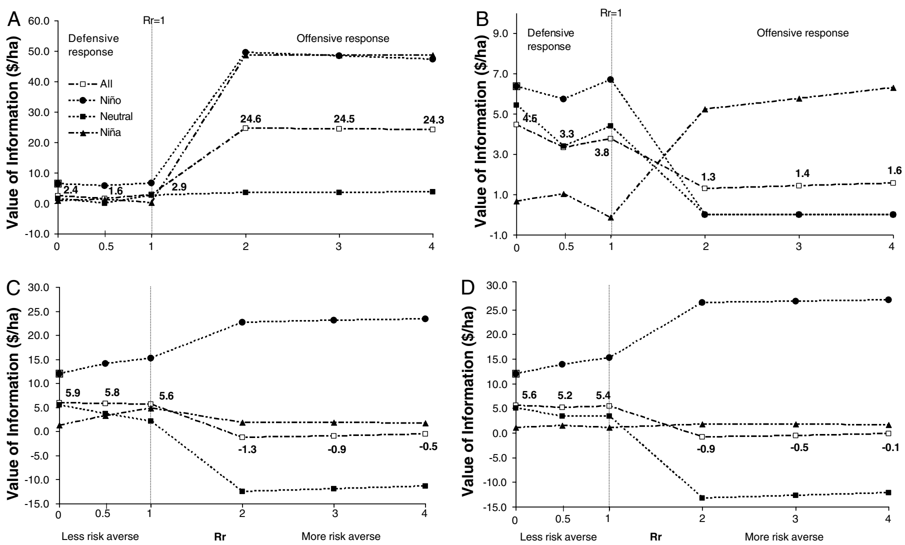

Fig. 4. Forecast value by ENSO phase and R_r level. Each EVOI estimated over a single 2970-year interval. EVOI expressed in certainty equivalent units (US\$ ha^{-1}). (A) Without applying farm programs. (B) Applying Commodity Loan Programs (CLP). (C) Applying Crop Insurance Programs (CIP). (D) Applying CLP and CIP. Numbers along with the curve indicate value of the information (\$ ha^{-1}) for all years.

a defensive response, while risk averse use forecast offensively. 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} for all years, 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 averse farmers when El Niño or La Niña events were forecast (\$48 ha^{-1}). For less risk averse 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. 4A).

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 \$2.40 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).

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. 5.

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 estimates. The probability of negative EVOI estimates in Fig. 5 is 831 out

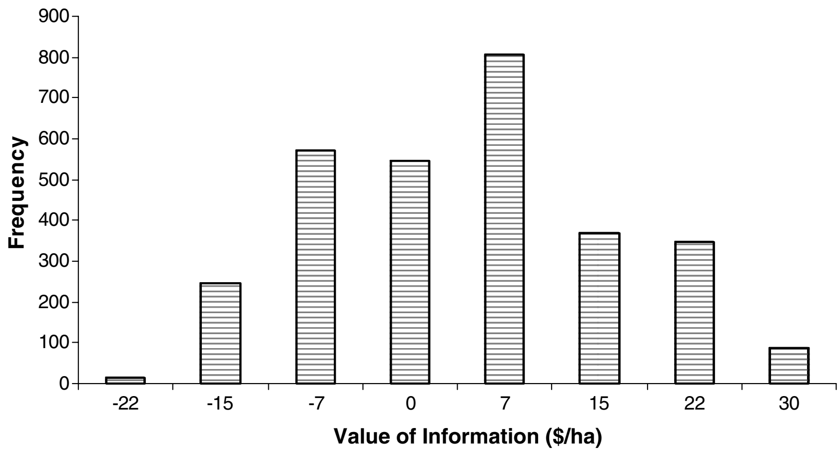

Fig. 5. Frequency distribution of EVOI estimates in 100-year horizons for the case of $R_r = 1$. Mean = \$4.39 ha^{-1} and 95% confidence interval = \$[3.48, 5.30] ha^{-1}.

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

Prices of peanut are still highly 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). It is expected that these peanut price incentives will disappear in the near future. Consequently, it is highly likely that the final prices received by peanut farmers will continue decreasing in the near future. The 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 US exports will remain marginal and not have major impacts on the domestic peanut prices. In order to study the impacts of peanut price reductions in our value of information portfolio, we arbitrarily reduced the prices of peanuts 33% and estimated the value of the information under those conditions. Results 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 Fig. 4A.

3.4. Forecast value with farm programs

3.4.1. Forecast value with Commodity Loan Programs

We followed similar analyses to the EVOI estimates when CLP were applied. Fig. 4B shows the relationship between ENSO phases, EVOI and R_r when CLP are included. Overall the value of the information is greatly reduced when CLP 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. This was the highest value of the information. For higher risk averse levels (>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; however it was zero for La Niña years and $R_r = 1$ and for El Niño and neutral years and >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.

3.4.2. Forecast value with Crop Insurance Programs

We followed similar analyses to the EVOI estimates when CIP were applied. Fig. 4C 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 $\$-5.60\ \mathrm{ha}^{-1}$. EVOI was negative ($\$-0.50\ \mathrm{ha}^{-1}$) for all years and $R_r > 2$ because it was highly negative ($<\$-11\ \mathrm{ha}^{-1}$) when neutral years. EVOI estimates for El Niño years and R_r were moderately high ($>\$22\ \mathrm{ha}^{-1}$). Still under CIP conditions high risk averse farmers could benefit by potential favorable conditions when El Niño years are forecast.

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 (ENSO independent) are unfavorable 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, we sampled 325 years for our optimization and then constrained the model to the optimal settings. Use of forecast could be a losing proposition when extreme prices and weather 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.

3.4.3. 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. 4D 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 the information, 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 $\$-0.10\ \mathrm{ha}^{-1}$ and $\$-0.90\ \mathrm{ha}^{-1}$. 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 ($\$26\ \mathrm{ha}^{-1}$) 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 impact the value of 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 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.

Forecast value is inherently probabilistic even for perfect ENSO phase forecasts and must be estimated and communicated as confidence intervals rather than a single point estimate. Our numerous synthetic prices and yields allowed us to generate probability 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).

Further research should include weather synthetic generators, other forms of farm programs, and similar representative farms in the neighboring states of Alabama and Georgia. Currently, a state of the art weather generator adaptable to North Florida conditions is being developed by a team of researchers at the University of Miami. Other farm programs such as direct payments, counter cyclical payments and taxes, would be useful to better represent the decision making environment that farmers face and identify more synergies and conflicts between climate information and farm programs that could be proactively used.

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