Impact of Climate Information on Reducing Farm Risk by Optimizing Crop Insurance Strategy

V. E. Cabrera, C. W. Fraisse, D. Letson, G. Podestá, J. Novak

Abstract. *Predictability of seasonal climate variability associated with the El Niño Southern Oscillation (ENSO) suggests a potential to reduce farm risk by selecting crop insurance products with the purpose of increasing farm income stability. A hypothetical 50% peanut, 50% cotton, non-irrigated, 40 ha (100 ac) north Florida farm was used to study the interactions of different crop insurance products with ENSO-based climate information and levels of risk aversion under uncertain conditions of climate and prices. Crop yields simulated by the DSSAT suite of crop models using multiyear weather data combined with historical series of prices were used to generate long series of stochastic income distributions in a whole-farm model portfolio. The farm model optimized planting dates and simulated uncertain incomes for 50 alternative crop insurance combinations for different levels of risk aversion under different planning horizons. Results suggested that incomes are greatest and most stable for low risk-averse farmers when catastrophic (CAT) insurance for cotton and 70% or 75% actual production history (APH) for peanut are selected in all ENSO phases. For high risk-averse farmers, the best strategy depends on the ENSO phase: (1) 70% crop revenue coverage (CRC) or CAT for cotton and 65% APH for peanut during EL Niño years; (2) CAT for cotton and 65%, 70%, or 75% APH for peanut during neutral years; and (3) 65% to 70% APH, or CAT for cotton and 70% APH for peanut during La Niña years. Optimal planting dates varied for all ENSO phases, risk aversion levels, and selected crop insurance products.*

Keywords. *Coefficient of relative risk aversion, El Niño Southern Oscillation, ENSO, Farm programs, Government intervention, Value of climate information.*

The El Niño Southern Oscillation (ENSO) is a strong driver of seasonal climate variability that impacts cotton and peanut crop yields in the southeastern U.S. (Hansen et al., 1998). ENSO-based climate forecasts have been shown to help reduce risks faced by agricultural enterprises (Hansen, 2002; Jones et al., 2000). Crop insurance is a major component of risk management that farmers could use together with climate information to maintain or increase their income stability (Changnon et al., 1999). Consequently, there is a need to study the potential interactions of ENSO-based forecasts and crop insurance strategies on the stability of farm income.

Several studies have addressed the impacts of crop insurance products on farm income (Sherrick et al., 2004; Coble et al., 2000; Wang et al., 1998) and the potential farm value of seasonal ENSO-based forecasts (Letson et al., 2005; Meza et al., 2003; Hammer et al., 2001). A few studies have explored the interactions between common crop insurance contracts and the farm value of ENSO-based forecasts (Cabrera et al., 2005; Mjelde and Hill, 1999; Mjelde et al., 1996). Yet, there is no research that systematically studies the impacts of the ENSO-based climate forecasts on the selection of crop insurance coverage.

Wang et al. (1998) determined yield and price levels that would trigger crop insurance indemnities under different contracts using expected utility optimization and simulation techniques in a representative Iowa corn farm; whereas Coble et al. (2000) found that yield-based crop insurance had a higher positive hedging impact than revenue-based insurance coverage. Sherrick et al. (2004) compared alternative parameterizations of corn and soybean crop-yield distributions to examine a limited set of crop insurance products. Other studies have also addressed the consequences of alternative crop insurance policies, but not the climatic impact on these decisions (Mahul and Wright, 2003; Chambers and Quiggin, 2002; Vercammen, 2000).

Letson et al. (2005) used a whole-farm decision framework to estimate the value of the ENSO-based forecast in the Argentinean pampas under intra-phase climate variability and uncertain prices; Meza et al. (2003) studied the value of El Niño phase forecasts for selected locations in Chile; and Hammer et al. (2001) synthesized experiences of economic use of ENSO-based forecasts in Australia, Zimbabwe, and Argentina. Other studies have also evaluated the economic value of ENSO-based forecasts, but not the consequences of

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The authors are **Victor E. Cabrera, ASABE Member,** Assistant Professor, College of Agriculture and Home Economics, Agricultural Science Center at Clovis, New Mexico State University; **Clyde W. Fraisse, ASABE Member,** Assistant Extension Scientist, Department of Agricultural and Biological Engineering, University of Florida, Gainesville, Florida; **David Letson,** Associate Professor, Marine Affairs and Policy, Rosenstiel School of Marine and Atmospheric Science, University of Miami, Miami, Florida; **Guillermo Podestá,** Research Associate Professor, Division of Meteorology and Physical Oceanography, Rosenstiel School of Marine and Atmospheric Science, University of Miami, Miami, Florida; and **James Novak,** Extension Economist and Professor, Agricultural Economics and Rural Society, University of Auburn, Auburn, Alabama. **Corresponding author:** Victor E. Cabrera, Agricultural Science Center at Clovis, New Mexico State University, 2346 SR 288, Clovis, NM 88101; phone: 505-985-2292, ext. 127; fax: 505-985-2419; e-mail: vcabrera@nmsu.edu.

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alternative crop insurance policies (Messina et al., 1999; Hill et al., 2000; Chen et al., 2002; Meza and Wilks, 2003).

Some studies have addressed the crop insurance policy impacts on the value of the ENSO–based climate forecasts. Mjelde et al. (1996) included the most common yield protection insurance policies and Mjelde and Hill (1999) included catastrophic crop insurance coverage in a corn/sorghum farm in east central Texas, whereas Cabrera et al. (2005) included the most common yield and revenue crop insurance policies in a cotton/peanut/corn farm. Mjelde et al. (1996) concluded that crop insurance had little effect on after–tax farm cash flows. Mjelde and Hill (1999) found that the inclusion of a catastrophic insurance program decreases the value of improved ENSO–based forecasts. Cabrera et al. (2005) found that the use of yield insurance for peanut and corn and revenue insurance for cotton also decreases the value of the climate information for north Florida farm conditions. These studies present the economics of including crop insurances with and without the consideration of ENSO–based forecasts. However, there are no studies dealing with an inclusive list of crop insurance products and a systematic process to select the best–performing crop insurance products in a whole–farm portfolio.

Crop insurance products have recently proliferated in the U.S. because of an increased interest in managing income risk by farmers, lenders, and congressional members (Wang et al., 2003). This trend is likely to continue because the Agricultural Risk Protection Act of 2002 provides financial incentives for the development of new insurance products and increases the insurance premium subsidies to encourage higher participation and coverage levels. Farmers currently have available multi–peril or actual production history yield insurance products that pay based on individual yield shortfalls, area yield insurance products that pay based on county yield shortfalls, and revenue insurance products that pay based on individual revenue shortfalls. In addition, premiums charged to farmers, which have historically included a fixed subsidy, have been modified to a regressive proportional subsidy that overall is significantly greater than in the past.

The objective of this study is to explore the impacts of ENSO forecasts and risk preferences on crop insurance selection on a non–irrigated, peanut–cotton farm in Jackson County, Florida. The main hypothesis is that the use of ENSO forecasts to select crop insurance products would increase or maintain farm income and income stability.

Materials and Methods

Representative Farm

The study was conducted on a hypothetical 40 ha (100 ac) non–irrigated farm in Jackson County, Florida (30.774° N, 85.226° W) that grows 50% peanut (*Arachis hypogaea* L.) and 50% cotton (*Gossypium hirsutum* L.). A dominant soil type used for agriculture in the region, Dothan loamy sand, was assumed for the farm. This specific case study has implications for crop insurance selection in many other parts of the southeast U.S. because of similarities in environment (e.g., climate, soils), resources (e.g., farm size, crops grown), and technology (e.g., rainfed agriculture).

Cotton and peanut are major cash crops in the southeast U.S., and non–irrigated farm enterprises are mostly affected by climate variability. Jackson County has a mean annual precipitation of 1466 mm (57.7 in.) and an average temperature of 19.3°C (66.8°F). The long–term average rainfall during the growing season (April to November) is 961 mm (37.8 in.), and the mean temperature is 22.8°C (73.1°F). The ENSO phases influence precipitation and to a lesser extent temperature in Jackson County during the growing season, but not in a consistent manner. 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). The Southeast Climate Consortium provides county–specific seasonal climate forecasts for three states (Florida, Alabama, and Georgia). Farmers and extensionists can obtain permanent update of these forecasts at: www.agclimate.org.

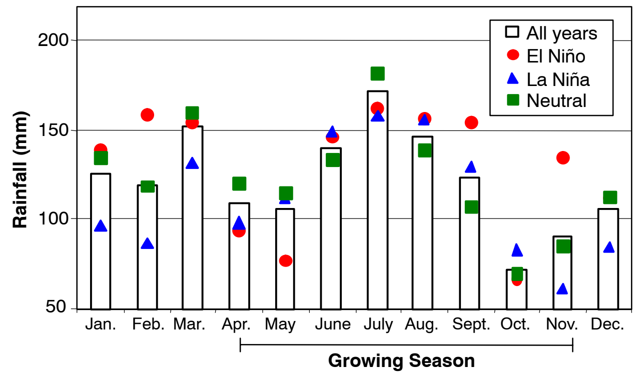

Figure 1. Historical (1950–2004) monthly rainfall in Jackson County, Florida, for El Niño, La Niña, and neutral ENSO phases compared to all years (source: www.agclimate.org).

Farm Model

Our model includes the influence of climatic, agronomic, and economic factors in a whole–farm stochastic decision and simulation system (fig. 2). First, the planting dates for each combination of ENSO phase, crop insurance, and risk aversion level are optimized. Then, the model sets these decision variables in the stochastic database to estimate uncertain incomes.

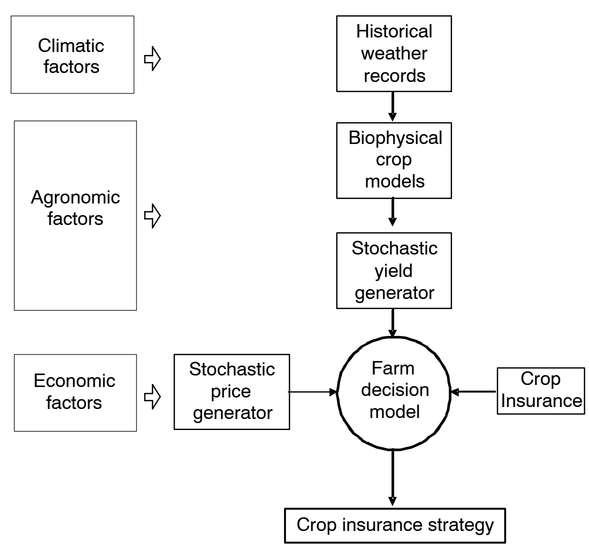

Figure 2. Simulation framework: climatic, agronomic, and economic components of the farm model (adapted from Letson et al., 2005, p. 168).

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

The climatic component of the model contains long series of weather records that are used to stochastically generate crop yields for each ENSO phase by re–sampling yields previously simulated by the crop component. Simulated crop yields are combined with stochastically generated crop prices to simulate farm income.

Available insurance products for cotton and peanut in Jackson County, Florida, were introduced in the model along with risk aversion levels to test the hypothesis that the selection of crop insurance based on ENSO forecasts may increase or maintain the stability of farm income. This study differs from previous approaches (Messina et al., 1999; Letson et al., 2005) in that it examines the risk associated with selection of crop insurance products, it includes a stochastic yield simulator, and the farm system analyzed has been regionally adapted to the southeast U.S.

Climatic Component

Daily rainfall and maximum and minimum temperatures for Jackson County from 1939 to 2003 (65 years) collected at the Chipley weather station (30.783° N, 85.483° W) were used to run crop yield simulations. A solar radiation generator, WGENR, with adjustment factors obtained for the southeastern U.S. (Garcia and Hoogenboom, 2005) was used to generate daily solar radiation data. During this period of time, 14 years were El Niño, 16 years were La Niña (table 1), and the remaining 35 years were neutral, according to the Japan Meteorological Index (JMA, 1991). ENSO phases run from 1 October of one year to 31 September of the next year. For this study, we only used the second year to designate each ENSO phase because cotton and peanut are planted between April and June. For example, in table 1, 1998 was an El Niño year that started in October 1997 and ran until September 1998.

Agronomic Component

Biophysical Crop Models

Crops yields were simulated using the models available in the Decision Support System for Agrotechnology Transfer (DSSAT) v4.0 (Jones et al., 2003). The CROPGRO–Peanut (Boote et al., 1998) and the recently developed CROPGRO–Cotton (Messina et al., 2005) were used. These models have been calibrated and tested for the management practices and environmental conditions found in the southeastern U.S. (Mavromatis et al., 2002; Messina et al., 2005). Crop model simulations used current management practices in the region for varieties, fertilization, planting dates (H. E. Jowers, County Extension Director IV, Jackson County Extension Office, Marianna, Fla.; personal communication, 28 Oct. 2004), and the representative soil type (Dothan loamy sand). In the case of peanut, the variety most widely planted in the region (Georgia Green) was used for the simulations. It is a runner–type variety with medium maturity and moderate resistance to tomato spotted wilt virus (TSWV) and to cylindricladium black rot (CBR). For cotton, a popular medium to full season variety (DP 555, Delta and Pine Land Co., Scott, Miss.) was used.

Nitrogen fertilization practices for the simulations followed local practices: 10 kg ha^{-1} at planting for peanut, and 110 kg ha^{-1} in two applications for cotton. Peanut is planted between mid–April and mid–June and cotton between mid–April and early May (table 2). Nine planting dates for peanut and four for cotton (about one week apart) were included in the simulations.

Stochastic Yield Generator

The limited duration of daily weather records provided only a few realizations of ENSO impacts on crop yields (i.e., only 14 El Niño realizations). However, a thorough assessment of climate risk 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 data (Letson et al., 2005; Meza et al., 2003) that were then used to predict agronomic and economic outcomes. A different approach consisting of a stochastic yield generator based on simulated crops yields was used in this study.

Our stochastic yield generator employed re–sampling in three steps. First, crop yields simulated by the models were sorted by ENSO phase and planting date. Second, a function

Table 2. Crops, varieties, planting dates and synthetic yields (means and standard deviations).

Crop (Variety)	Planting Date	Synthetic Yields (kg ha^{-1}), mean (SD) All years (n = 2970)	El Niño (n = 990)	Neutral (n = 990)	La Niña (n = 990)
Peanut	16 April	3078 (1275)	2918 (1308)	3261 (1507)	3055 (916)
(Georgia Green)	23 April	3150 (1276)	3077 (1339)	3151 (1471)	3221 (961)
	1 May	3217 (1272)	3150 (1232)	3202 (1474)	3298 (1076)
	8 May	3332 (1318)	3303 (1235)	3338 (1430)	3356 (1282)
	15 May	3360 (1225)	3313 (1146)	3278 (1257)	3489 (1260)
	22 May	3361 (1210)	3390 (1064)	3352 (1248)	3341 (1305)
	29 May	3373 (1266)	3402 (1224)	3371 (1201)	3346 (1368)
	5 June	3341 (1327)	3440 (1389)	3288 (1238)	3296 (1344)
	12 June	2956 (1477)	3008 (1613)	2982 (1376)	2877 (1429)
Cotton	16 April	720 (78)	720 (78)	729 (84)	711 (69)
(DP 555)	23 April	717 (81)	707 (79)	736 (80)	709 (81)
	1 May	714 (84)	699 (89)	733 (70)	711 (89)
	8 May	715 (76)	696 (60)	727 (72)	722 (89)

(logarithmic, exponential, quadratic, or linear; whichever had a higher R^2) was fit to the data. This mathematical function was used to predict yields in order to avoid underestimating potential extreme values in the distribution. Third, yields were stochastically generated by re−sampling from the function to produce 990 realizations of crop yields for each ENSO phase. The procedure was repeated for each combination of crop, planting date, and ENSO phase. Table 2 shows means and standard deviations of synthetically generated crop yields across ENSO phases and planting dates.

Economic Component

Stochastic Price Generator

In order to match simulated yields, 2970 price series for each crop (peanut and cotton) were stochastically generated by simulating a multivariate distribution respecting price covariance between crops based on historical price variability. The procedure followed the methodology by Letson et al. (2005). First, monthly average prices (Jan. 1996 to Jan. 2005) received by Florida farmers for peanut and cotton were obtained from the USDA National Agricultural Statistical Service (www.nass.usda.gov/fl/econ/prices/), converted to $ Mg^{-1} units, and the peanut−cotton price correlation structure was estimated and evaluated. Second, prices were deflated to January 2005 dollars using the U.S. Consumer Price Index, and the data were de−trended for seasonal differences by estimating monthly residuals with respect to their means. Finally, principal component analysis was used to decompose the matrix of price residuals into three uncorrelated time series of amplitudes that were separately sampled, recombined, and back−transformed to reconstruct crop price residuals. Kolgomorov−Smirnov tests confirmed that the correlation structure of the synthetic price residuals was similar to that of the historical data. Quantile−quantile plots were used to ensure that historical price distributions were well reproduced. Seasonal price averages for the harvesting dates of the three crops (2 Sept. to 6 Nov. for peanut, and 22 Sept. to 28 Dec. for cotton) were re−introduced. It should be noted that the generated price distributions are not historical values, but distributions consistent with historical variability. The correlation between deflated prices of cotton and peanut was 0.472. The means of the synthetic prices were 1385 $ Mg^{-1} for cotton and 626 $ Mg^{-1} for peanut. The standard deviations of the synthetic prices were 69 $ Mg^{-1} for cotton and 125 $ Mg^{-1} for peanut.

Production Costs

Variable and fixed production costs by crop were considered in the model. Contemporary local costs of production and labor requirements for the two crops were provided by the North Florida Research and Education Center (J. Smith and T. Hewitt, Enterprises Budgets, Quincy, Fla.; personal communication, 23 Nov. 2004). The variable costs were 1088 $ ha^{-1} for peanut and 1122 $ ha^{-1} for cotton. The fixed costs were 344 $ ha^{-1} for peanut, 177 $ ha^{-1} for cotton.

Farm Decision Model

A stochastic non−linear whole−farm model was used to study the role of climate forecasts in decision making and to estimate the impact of crop insurance choices on the farm income. The model was systematically solved to identify optimal planting dates and to simulate annual incomes for all combinations of ENSO phases (and all years), available crop insurance products, and risk aversion levels.

Optimal Farm Decisions

The model selected optimal planting dates for cotton and peanut (table 2) assuming 50% of the land devoted to each crop (C. Smith, Jackson County Extension Office, Marianna, Fla.; personal communication, 10 June 2005). This procedure was repeated for each combination of peanut and cotton crop insurance products. The model maximized the expected utility (U) for a one−year planning period (eqs. 1 to 3):

$$\max_x E\{U(W_f)\} = \sum_{n=1}^{N} U(W_0 + \Pi_{i,n})/N \quad \text{for } i = 1, 2, 3, 4 \tag{1}$$

$$\Pi_{i,n} = \sum_{j=1}^{2} Y_j P_j X_j + IY_j PB_j X_j - C_j X_j - Pr_j X_j \quad \text{for } n = 1 \text{ to } N, \;\; i = 1, 2, 3, 4 \tag{2}$$

$$\sum_{m=1}^{9} X_{m,j} = 0.5 \quad \text{for } j = 1$$
$$\sum_{m=10}^{13} X_{m,j} = 0.5 \quad \text{for } j = 2$$
$$X_m \ge 0 \tag{3}$$

where

i = ENSO phase and all years (1 = El Niño, 2 = neutral, 3 = La Niña, 4 = all years)
j = crop (1 = peanut, 2 = cotton)
m = planting date in table 2 (1 to 9 for peanut, and 10 to 13 for cotton)
n = years for each optimization (1 to 990 for El Niño, 991 to 1980 for neutral, 1981 to 2970 for La Niña, and 1 to 2970 for all years)
Π = income
W_0 = initial wealth
W_f = final wealth
Y = yield
IY = indemnity yield for insurance purposes (i.e., the compensation a farmer receives to cover losses below insured yield levels)
P = price
PB = price base for insurance purposes
C = production cost
Pr = insurance premium
X = land allocation for every crop planting date.

The MINOS5 algorithm in GAMS (Gill et al., 2000) was used along with a randomized procedure to alter starting values and ensure global maxima solutions. Every solution identified planting dates that maximized expected utility.

Constant Risk Aversion Coefficient

Utility is also a power function of wealth, based on a constant risk aversion coefficient (R_r), according to Hardaker et al. (2004). Equation 4 introduces five plausible levels of risk aversion considering the cases of "risk taker" (R_r = 0), "normal aversion" (R_r = 1), "rather averse" (R_r = 2), "very averse" (R_r = 3), and "almost paranoid" (R_r = 4):

$$U\left(W_f\right) = \frac{W_f^{1-R_r}}{1-R_r} \quad \text{for } R_r = 0, 1, 2, 3, 4 \tag{4}$$

Letson et al. (2005) indicates that responses to forecast information can be "defensive" when the response is used primarily to avoid risk associated with potential adverse conditions or "offensive" when the response is used primarily to seek more profits by taking advantage of potential favorable conditions. Risk taker and normal risk−averse farmers (low risk−averse, R_r = 0, 1) employ a defensive response, while risk−avoiding farmers (R_r = 1, 2, 3) employ an offensive response. In addition, larger farms are less risk averse.

Farm Simulation and Income Calculation

We constrained the farm model to optimal planting date allocations to simulate income for every ENSO phase (990 for each ENSO phase) and for all years (2970 years) using all synthetic yields and prices. This procedure was repeated for each combination of crop insurance products and level of risk aversion (R_r). Income for each year was estimated and compared across ENSO phases and crop insurance products.

Crop Insurance Products Available for Peanut and Cotton Growers

In order to test realistic farm scenarios, the most commonly used insurance options available for cotton and peanut growers in Jackson County, Florida, were introduced into our decision modeling. Crops are indemnified under separate policies. Therefore, information was gathered on: (1) types of insurance used for alternative crops, (2) levels of coverage available for the crops, (3) indemnity price base, and (4) policy premiums for available policies (table 3).

Actual production history (APH) crop insurance, also called multiperil crop insurance (MPCI), insures a percentage of the farmers' historical yield. If the yield becomes lower than the insured percentage, then the insurance pays an indemnity that covers the difference between the insured percentage and the low yield. To convert the indemnity yield to monetary value, a price selected by the farmer is used. This price is selected as a percentage (55% to 100%) of a base price established by the government.

A relatively new insurance product, crop revenue coverage (CRC), insures income by indemnifying farmers based on historical yield and market prices. If the actual yield multiplied by the greater of an established price or actual market price at harvest time is lower than an indemnified income level, then the farmer is entitled to an insurance payment.

Level of coverage indicates the percentage of yield or income insured as elected by the farmer. For APH peanut and cotton insurance, farmers can protect between 50% and 75% of their yields. For CRC, only available for cotton, farmers can protect between 50% and 85% of income and 55% to 100% of price. In both cases, APH and CRC, the percentage of coverage is selected in 5% increments within these ranges. This study examines the most commonly used yield protection levels (65% to 75%) and income protection levels (65% to 85%) (table 3). Catastrophic coverage (CAT) is available for both crops and is a special case of insurance coverage, which otherwise can be defined as an APH policy at 50% yield coverage with 55% price base election.

Table 3. Crop insurance products, coverage levels, premium prices, and average yields used in the farm model analysis.

	Peanut	Cotton
APH coverage range (5% increments)	65% to 75%	65% to 75%
CRC coverage range (5% increments)	--	65% to 85%
Price base 2004 ($ kg^{-1})	0.3935	1.4991
APH premium range 2004 ($ ha^{-1})	9.64 to 41.27	21.50 to 93.90
CRC premium range 2004 ($ ha^{-1})	--	27.18 to 288.87
Average yield (Mg ha^{-1})	3.362	0.729

Policy premiums are county−specific and depend on several conditions, such as type of insurance, level of coverage, price election, and some management characteristics (historical yields, irrigation, etc.). The Risk Management Agency (USDA−RMA) web−based tool (www3.rma.usda.gov/apps/premcalc/) was used to calculate premiums for all insurance options using information for the most recent year (2004). In order to limit the number of options and reflect the most common scenarios, premiums were calculated using 100% of price base election for all cases, with the exception of CAT. Technically, there is no premium for CAT coverage. An "administrative fee" is charged, which is independent of the planted area. This fee is currently fixed at US$100 per crop for Jackson County. Consequently, for our 20 ha cotton / 20 ha peanut farm, the CAT premium was assumed to be US$100 per crop or US$5.00 per ha per crop.

The case of not taking insurance for either or both crops is a valid option and was also considered in the crop insurance combinations. Fifty crop insurance scenarios, resulting from the combination of five options for peanut and ten options for cotton, were included in the analyses.

Results and Discussion

Farm Income Under Risk−Taker Conditions (R_r = 0)

A complete analysis of all possible combinations of crop insurance products was performed under risk−taker conditions. This analysis was used as a first step to screen out the insurance combinations with a better potential for maintaining or increasing income. A statistical t−test (α = 0.05) divided incomes into nine categories for all the combinations of crop insurance products for a single 990−year planning horizon. Seven of these categories were at the lower end and were clustered together as low incomes. Figure 3 shows three well−defined zones of statistically different incomes: zone 1 of low incomes, zone 2 of medium incomes, and zone 3 of high incomes. Low incomes were reported for insurance combinations where the highest CRC policy (85%) was selected for cotton, followed by those incomes that occurred when cotton had 80% CRC or 75% APH and peanut had either CAT, the no insurance option, or 65% APH. Medium incomes happened for a larger number of policy combinations that included all possible insurance policies for both crops, excluding those combinations where there would be very low coverage for cotton along with medium to high coverage for peanut. The third category, with the highest incomes, included insurance combinations with low (CAT) or no coverage for cotton along with medium to high coverage for peanut (65% to 75% APH). The highest income occurred when no insurance was selected for cotton and 75% APH was selected for peanut.

Resulting higher incomes for the cases of low or no insurance coverage for cotton may be a consequence of more

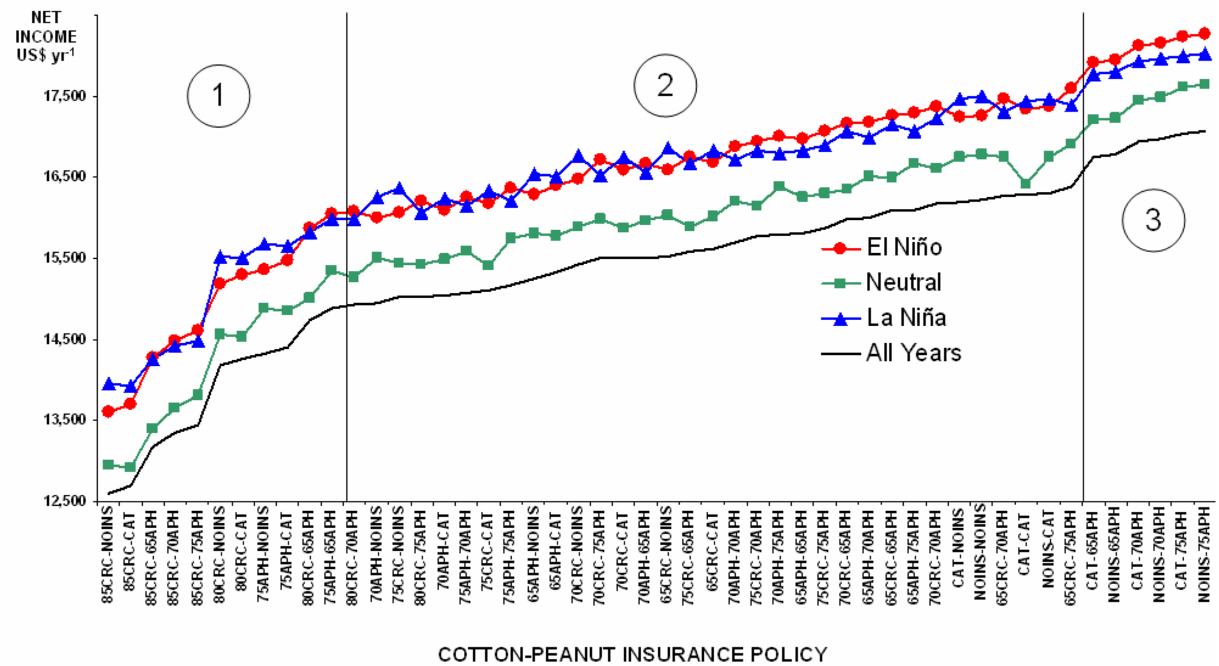

Figure 3. Average simulated income of a north Florida farm (40 ha; 50% cotton / 50% peanut) under risk–taker conditions (R_r = 0) for 50 combinations of crop insurance products according to ENSO phases sorted by "all years." Scenarios indicate cotton–peanut insurance combination: CRC = crop revenue coverage, APH = actual production history, CAT = catastrophic coverage, and NOINS = no insurance coverage (e.g., 70CRC–75APH denotes 70% crop revenue coverage for cotton and 75% actual production history for peanut).

expensive premiums for cotton insurance as compared to peanut insurance, and the fact that cotton yields are less variable than those of peanut. The option of buying cotton insurance may not enter the choice set of those who are risk takers or normal risk takers.

Incomes by ENSO Phase for Different Crop Insurance Coverages

A statistical t–test (α = 0.05) indicated that there were significantly higher incomes during El Niño and La Niña years than during neutral years. Between El Niño and La Niña years, there were no significant differences. The lowest incomes were expected for "all years," as seen in figure 4, because these do not include decisions based on forecasts; consequently, the income difference between any ENSO phase and "all years" is the value of using climatic information.

Higher incomes were simulated for low or no insurance coverage for cotton combined with high coverage for peanut, independently of ENSO phase. The highest income (US\$ year^{-1}) was obtained during El Niño years with the no insurance option for cotton and 75% APH for peanut (average = 18,265 and 95% CI = [17,027–19,502]). The lowest income was obtained for neutral years when the 85% CRC coverage was selected for cotton and no insurance was selected for peanut (average = 12,947 and 95% CI = [11,741–14,154]). The curves representing income during El Niño and La Niña years in figure 3 cross over at several points, indicating the opportunity of selecting different crop insurance combinations to reach higher incomes according to El Niño or La Niña forecasts.

Distribution of Incomes

Results presented in previous sections included the average income for distributions of uncertain climate and prices for 990 records for each one of the ENSO phases and for 2970 records for all years. However, it must be understood that the results are probabilistic distributions that include all the potential combinations of climate and prices by ENSO phase.

Figure 4 presents the frequency distribution of income for four combinations of crop insurance products. In all cases, the probability of negative income exists; however, it is substantially higher for the combination of 85% CRC for cotton and 65% APH for peanut (low income location) and substantially lower for the selection of 65% CRC for cotton and 75% APH for peanut (medium income location), consistent with their averages values (fig. 3). Distributions for combinations 1 and 4 were skewed to the left and, in these, the curve for La Niña years had negative kurtosis, indicating a flatter tendency in its distribution. In most of the cases, the maximum and minimum values were contained in the neutral distribution curves; however, the maximums for selections 2 and 3 occurred for El Niño years.

Optimal Planting Dates

The optimization model indicated high incomes for all years when cotton was planted on 16 April and peanut on 29 May. For El Niño years, the best planting dates were 16 April and 5 June; for neutral years, these were 23 April and 8 May; and for La Niña years, these were 8 May and 15 May. These optimal planting dates remained for all the combinations of crop insurance products with the exception of peanut in neutral years, which had an optimal planting date of 29 May when either CAT or the no insurance option was selected for this crop.

Best–Performing Crop Insurance Combinations Under Different Risk Aversion Levels (R_r = 0 to 4)

The best–performing crop insurance combinations were analyzed under different risk aversion levels. Farmers might

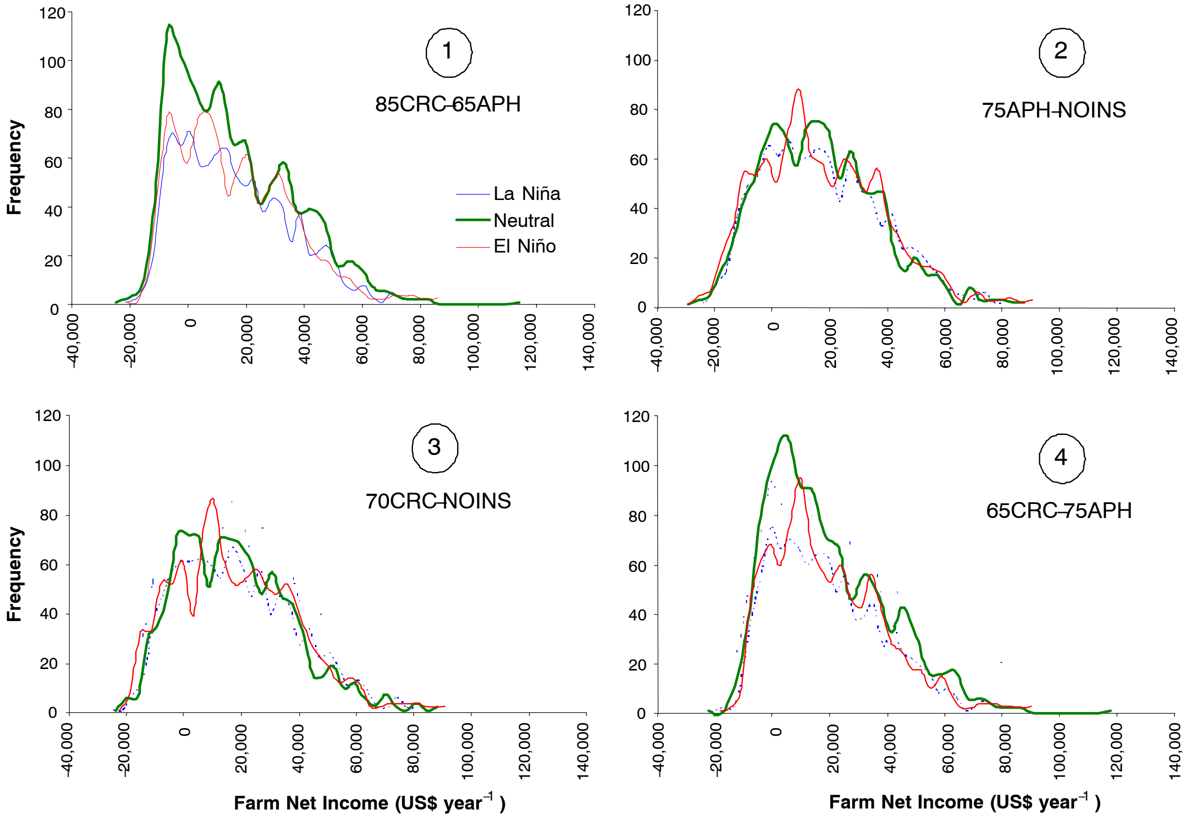

Figure 4. Farm income distribution by ENSO phase for four selected crop insurance combinations for R_r = 0. Scenarios indicate cotton−peanut insurance combination: CRC = crop revenue coverage, APH = actual production history, and NOINS = no insurance coverage.

Table 4. Five top crop insurance combinations according to average incomes by ENSO phase and level of risk aversion.

	El Niño		Neutral		La Niña	
R_r[a]	Insurance[b] (cotton−peanut)	Avg. Income (\$ year^{-1})	Insurance[b] (cotton−peanut)	Avg. Income (\$ year^{-1})	Insurance[b] (cotton−peanut)	Avg. Income (\$ year^{-1})
0	NOINS−75APH	18,265	NOINS−75APH	17,641	NOINS−75APH	18,022
	CAT−75APH	18,235	CAT−75APH	17,611	CAT−75APH	17,992
	NOINS−70APH	18,148	NOINS−70APH	17,482	NOINS−70APH	17,951
	CAT−70APH	18,114	CAT−70APH	17,451	CAT−70APH	17,918
	NOINS−65APH	17,943	NOINS−65APH	17,231	NOINS−65APH	17,791
1	NOINS−75APH	17,561	NOINS−75APH	17,085	NOINS−75APH	17,346
	CAT−75APH	17,530	CAT−75APH	17,054	CAT−75APH	17,317
	NOINS−70APH	17,420	NOINS−70APH	16,887	NOINS−70APH	17,246
	CAT−70APH	17,393	CAT−70APH	16,902	CAT−70APH	17,219
	NOINS−65APH	17,205	NOINS−65APH	16,653	NOINS−65APH	17,068
2	CAT−65APH	15,553	CAT−70APH	15,543	NOINS−70APH	15,086
	NOINS−65APH	15,356	CAT−65APH	15,213	CAT−70APH	15,028
	NOINS−NOINS	15,215	NOINS−65APH	15,066	65CRC−70APH	14,806
	70CRC−65APH	14,967	CAT−75APH	14,948	70CRC−70APH	14,581
	CAT−NOINS	14,966	CAT−NOINS	14,841	70APH−70APH	14,144
3	CAT−65APH	14,905	CAT−70APH	14,768	NOINS−70APH	14,452
	NOINS−65APH	14,713	CAT−65APH	14,407	CAT−70APH	14,392
	NOINS−NOINS	14,391	CAT−75APH	14,330	65CRC−70APH	14,202
	70CRC−65APH	14,359	NOINS−65APH	14,267	70CRC−70APH	13,989
	65CRC−65APH	14,219	CAT−NOINS	14,089	70APH−70APH	13,506
4	CAT−65APH	14,276	CAT−70APH	14,016	NOINS−70APH	13,832
	NOINS−65APH	14,089	CAT−75APH	13,731	CAT−70APH	13,772
	70CRC−65APH	13,770	CAT−65APH	13,625	65CRC−70APH	13,613
	65CRC−65APH	13,624	NOINS−65APH	13,492	70CRC−70APH	13,411
	NOINS−NOINS	13,587	CAT−NOINS	13,355	75CRC−70APH	12,894

[a] R_r is coefficient of risk aversion.
[b] Insurance is cotton−peanut insurance combination: CRC = crop revenue coverage, APH = actual production history, CAT = catastrophic coverage, and NOINS = no insurance.

respond differently depending on if they are risk takers (low risk–averse) or risk avoiders (high risk–averse). The same procedures applied to risk taker (R_r = 0) were applied to risk normality (R_r = 1) and higher risk aversion levels (R_r = 2, 3, 4). For practicality and simplicity, table 4 presents the top five crop insurance selections in descending order (higher incomes for a single 990–year planning horizon) by ENSO phase and risk aversion level. The yearly average predicted income decreased, as expected, with increased risk aversion levels.

For R_r = 0 and 1, the optimization indicated the same top best crop insurance combinations, and these remained across ENSO phases. The analysis suggested no coverage or CAT coverage for cotton and 65% to 75% APH for peanut under the risk taker (R_r = 0) and normal (R_r = 1) risk aversion levels. The suggested planting dates for both crops varied across ENSO phases. For the case of risk normality (R_r = 1), two or more optimal peanut planting dates were suggested (table 5).

For higher risk aversion levels (R_r = 2, 3, 4), the five top crop insurance combinations differed across ENSO phases and risk aversion levels. For cotton, although no insurance and CAT coverage were maintained in the list of best insurance combinations, higher coverage levels, such as 65% and 70% CRC for El Niño years and 65% to 75% CRC for La Niña years, were also included to account for higher risk aversion levels. For peanut, however, lower coverage levels were selected, such as no insurance and 65% APH for El Niño years, no insurance and 65% to 75% APH for neutral years, and 70% APH for La Niña years. Crop insurance coverage is just one of the ways that farmers can reduce exposure to risk. Peanut is fairly resistant to changes in the extremes of its yield variability, and major impacts in production due to diseases and nematodes can be managed at a lower cost than the insurance premium. We expect the more risk–averse decision maker to hedge, but that does not necessarily mean that the decision maker will buy more crop insurance. The tradeoff is increased financial risk versus reduced production risk. For the case of peanut, the risk–averse person would find that the cost of insurance is riskier than the additional protection provided by the insurance.

The best planting dates in the case of high risk aversion levels varied substantially from those of lower risk aversion levels. Planting dates varied depending on ENSO phases, risk aversion levels (R_r = 2, 3, and 4), and combination of selected crop insurance products.

Shorter–Term Planning Horizons (R_r = 0 to 4)

Estimates of income in the preceding sections assumed long–term planning horizons of 990 years (i.e., mean income of 990 years). However, a thorough assessment of risk should include a rationale more in tune with what farmers would use in their risk avoidance strategies, such as planning horizons of one or five years. Rather than only the expectance of higher incomes in the long run, farmers would be interested in reducing their risk of losses in the short or medium term. Having the results for long planning horizons as a reference, we can study which insurance combinations would better help to increase or maintain farm economic stability by decreasing the risk of economic losses in the short– to medium–term planning horizons. One–year planning horizons are of practical importance since they allow the inclusion of seasonal ENSO climate forecasts in the decision making process. For one–year planning horizons, the probability of economic failure increases substantially due to uncertainty in prices and climate (intra–phase variability).

Risks of losses expressed as probability of negative incomes were calculated using distributions of five– and one–year planning horizons and compared among crop insurance combinations. The shorter the planning horizon, the greater the likelihood of negative incomes. The number of negative incomes for the top five crop insurance combinations ranged from 0 to 8 (out of 180) in the case of five–year planning horizons, while it ranged from 106 to 245 (out of 990) for one–year planning horizons. The analysis revealed the same top crop insurance combinations as table 4, although farmers would consistently decrease their risk of income loss in the medium– and short–term planning horizons by purchasing some type of crop insurance rather than having no coverage. In table 4, there were no significant differences in income among top crop insurance combina–

Table 5. Two best–performing crop insurance combinations and planting dates by ENSO phase and risk aversion level when including short– and medium–term planning horizons.

	El Niño		Neutral		La Niña	
R_r[a]	Insurance[b] (cotton–peanut)	Cotton–Peanut Planting	Insurance[b] (cotton–peanut)	Cotton–Peanut Planting	Insurance[b] (cotton–peanut)	Cotton–Peanut Planting
0	CAT–75APH	16 April–5 June	CAT–75APH	23 April–8 May	CAT–75APH	8 May–15 May
	CAT–70APH	16 April–5 June	CAT–70APH	23 April–8 May	CAT–70APH	8 May–15 May
1	CAT–75APH	16 April[c]	CAT–75APH	23 April[d]	CAT–75APH	8 May–15 May
	CAT–70APH	16 April[c]	CAT–70APH	23 April[e]	CAT–70APH	8 May–15 May
2	CAT–65APH	23 April–29 May	CAT–70APH	23 April–16 April	CAT–70APH	23 April–29 May
	70CRC–65APH	23 April–29 May	CAT–65APH	23 April–16 April	65CRC–70APH	8 May–29 May
3	CAT–65APH	23 April–29 May	CAT–70APH	23 April–16 April	CAT–70APH	23 April–29 May
	70CRC–65APH	23 April–29 May	CAT–65APH	23 April–16 April	65CRC–70APH	8 May–29 May
4	CAT–65APH	23 April–23 Apr	CAT–70APH	1 May–16 April	CAT–70APH	23 April–16 April
	70CRC–65APH	1 May–23 Apr	CAT–75APH	1 May–16 April	65CRC–70APH	8 May–1 May

[a] R_r is coefficient of risk aversion.
[b] Insurance is cotton–peanut insurance combination: CRC = crop revenue coverage, APH = actual production history, CAT = catastrophic coverage, and NOINS = no insurance.
[c] 14% 29 May and 86% 5 June.
[d] 19% 16 April, 48% 8 May, 10% 22 May, and 24% 29 May.
[e] 16% 16 April, 45% 8 May, 12% 22 May, and 28% 29 May.

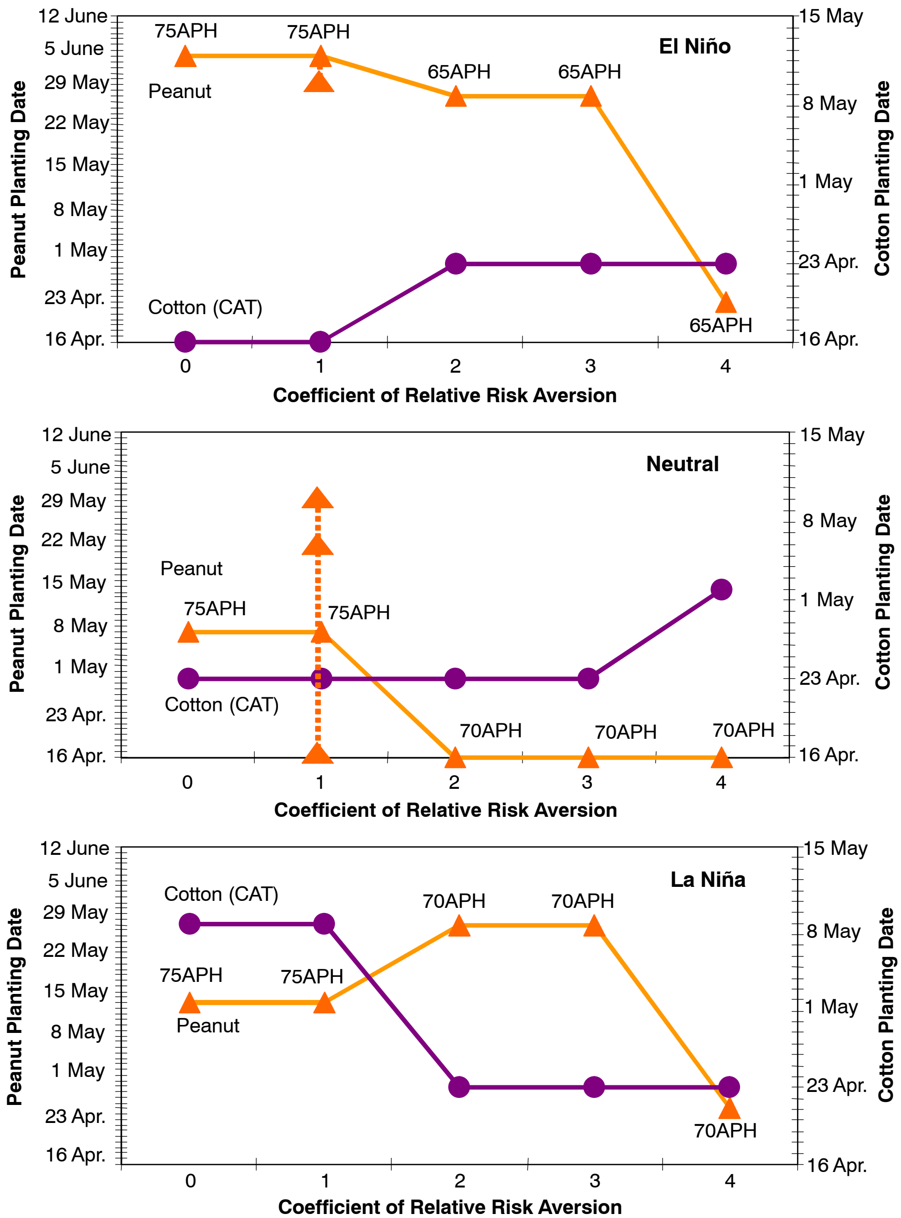

Figure 5. Best–performing crop insurance and planting dates for cotton and peanut growers by ENSO phase and risk aversion level for short– and medium–term planning horizons (APH is actual production history and CAT is catastrophic coverage).

tions (α = 0.05) by category of ENSO phase and risk aversion level (R_r). However, there were decreased risks of negative incomes for those including some type of crop insurance compared to those with no insurance at all.

For example, the option of no insurance for both crops, when compared to 70% CRC for cotton and 65% APH for peanut, had 2.33 times more likelihood of negative incomes during an El Niño phase for the case of five–year planning horizons and very high risk aversion (R_r = 4). The proposition of CAT for cotton and no insurance for peanut resulted in an increase of 23% in the chance of negative incomes when compared to CAT for cotton and 75% APH for peanut for the case of one–year planning horizons, R_r = 2, and neutral years. The combination of no insurance for cotton and 65% APH for peanut had 13% higher risk of negative incomes in one–year planning horizons than the combination of CAT for cotton and 75% APH for peanut for risk neutrality (R_r = 0) and La Niña years.

Consequently, there is a consistent advantage in relying on some kind of crop insurance coverage over no coverage in the short– and medium–term planning horizons for all risk aversion levels and ENSO phases. This fact is corroborated by an increasing pressure on farmers by lenders and government disaster relief agencies to always buy at least some type of crop insurance coverage.

Based on the results discussed above, the best–performing crop insurance combinations with short–term security and long–term income by ENSO phase and risk aversion level were selected. Table 5 lists the two best crop insurance products, and figure 5 shows the best crop insurance products together with the optimal planting dates for each case.

Less risk–averse farmers (R_r = 0, 1) would maintain or increase their income stability by selecting CAT for cotton and 70% or 75% APH for peanut; while optimal planting dates would depend on ENSO phases. Early planting

(16 April) in El Niño years and late planting (8 May) in La Niña years are recommended for cotton. Late planting (29 May to 5 June) in El Niño years and medium planting (15 May) in La Niña years are recommended for peanut. These results are in accordance with a study by Fraisse et al. (2005) that explored the use of ENSO phases for peanut crop insurance selection.

High risk−averse farmers (R_r = 2, 3, 4) would maintain or increase their income stability by selecting CAT or 70% CRC for cotton and 65% APH for peanut in El Niño years, CAT for cotton and 65% to 75% APH for peanut in neutral years, and CAT or 65% CRC for cotton and 70% APH for peanut in La Niña years. The recommended optimal planting dates for cotton are between 23 April and 1 May in El Niño and neutral years and between 23 April and 8 May in La Niña years. For peanut in El Niño years, the optimal planting dates are 29 May for risk aversion levels of 2 and 3, and 23 April for risk aversion level 4. In La Niña years, recommended optimal peanut planting dates are 29 May for risk aversion levels 2 and 3, and 23 April and 1 May for risk aversion level 4.

Conclusions

The use of ENSO−based forecasts (El Niño, La Niña, and neutral years) to select crop insurance products showed consistently increased farm incomes compared to the use of climatology (historical climate information). The inclusion of realistic planning horizons of one year and five years demonstrated the benefits of having at least some crop coverage over no insurance at all and allowed selection of the best insurance combinations by ENSO phase and level of risk aversion.

Because of higher premium costs and low inter−annual yield variability, low coverages for cotton were selected, which increased moderately with risk aversion levels (i.e., risk avoiders would select greater coverage than risk takers). For the case of peanut, high coverage levels were suggested, which decreased moderately with risk aversion levels (i.e., risk takers would select higher coverage than risk avoiders). High risk−averse farmers would find that the cost of the insurance premium for peanut is riskier than the additional protection provided by the insurance. Nevertheless, crop insurance selection for peanut affected the selection coverage for cotton, and vice versa, because our stochastic decision modeling analyzed the farm system as a whole, in which the overall optimized farm income had feedback from any individual decision.

The best crop insurance strategy for risk takers or less risk−averse farmers (R_r = 0, 1) to maintain or increase farm income was a combination of catastrophic insurance for cotton (50% yield at the 55% price base) and 75% or 70% actual production history (multi−peril crop insurance) for peanut across ENSO phases. Optimal cotton planting dates varied from early for El Niño years to medium in neutral years and to late for La Niña years, and optimal peanut planting dates varied from late for El Niño years to medium for neutral and La Niña years.

The best crop insurance strategy for risk avoiders or high risk−averse farmers (R_r = 2, 3, 4) to maintain or increase farm income were: for an El Niño year, a combination of catastrophic insurance or 70% crop revenue coverage for cotton and 65% actual production history for peanut; for a neutral year, a combination of catastrophic insurance for cotton and 65% to 75% actual production history for peanut; and for a La Niña year, a combination of catastrophic insurance, 65% or 70% crop revenue coverage, or 70% actual production history for cotton and 70% actual production history for peanut. The suggested planting dates for these selections varied depending on ENSO phase, risk aversion level, and the combination of crop insurance levels selected. For example, for an El Niño year, for cotton, early planting dates are selected, while for peanut, late planting dates are selected for R_r = 2, 3, and early planting dates for R_r = 4.

The decision framework presented in this article adds another dimension to the selection of crop insurance products by including criteria according to ENSO phase and risk aversion level. Estimated incomes by ENSO phase and crop insurance policies have to be understood and communicated as probabilistic distributions rather than point estimates because there will always be uncertainty in the prices and in climate (intra−phase variability).

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