USING CROP INSURANCE TO MANAGE CLIMATE-BASED FARM RISK: COMPARING THE CASES OF INSURERS AND FARMERS

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ABSTRACT

This study illustrates the potential synergies and conflicting interests between farmers and insurers in the selection of an optimal crop insurance contract. Special attention is given to how climate information influences this decision-making process. We consider a representative 40-ha, rainfed, cotton-peanut farm located in Jackson County, FL. Results show that year-to-year El Niño Southern Oscillation (ENSO)-based climate variability affects farmers' and insurers' net returns according to crop insurance contracts. Introduction of ENSO-based climate forecasts presents a significant impact on the selection of a particular contract to both the farmer and the insurer. We conclude that insurers and farmers can bridge their divergent interests by improving their understanding of the effect of climate conditions on the development of sustainable business plans.

INTRODUCTION

Climate variability significantly affects agricultural production, profitability, and risk (Chen and Chang, 2005; Mendelsohn et al., 2006). Prediction of seasonal climate variations can help reduce farm risk by tailoring agricultural management strategies to mitigate the impacts of adverse conditions or to take advantage of favorable conditions (Hill and Mjelde, 2002; Letson et al., 2005). Recently, researchers and policy makers have tried to coordinate strategies for risk management by expanding the variety of crop insurance products and by communicating usable and timely climate forecast information (Cabrera et al., 2006). Crop insurance offers farmers greater economic stability under the uncertainty of future random events, including climate variability (Mahul, 2001). However, the optimal crop insurance choices for farmers differ from those that would be optimal for insurers. In addition, once farmers buy crop insurance, they have a greater incentive to engage in risky behavior; clearly moral hazard can cause a divergence of interests between farmers and insurers. Predictions of climate variation may offer an opportunity to close this gap.

Most empirical studies on climate and crop insurance have focused on evaluating ways to reduce the farm risk associated with climate variability by selecting the most adequate crop insurance products. Among these studies Mjelde et al. (1996) implemented a decision-making framework to introduce crop insurance programs along with climate forecast information. Mjelde and Hill (1999) then developed a catastrophic insurance study for corn (*Zea mays* L.) and sorghum (*Sorghum bicolor* [L.] Moench) using utility functions under uncertain weather forecasts. Schneider and Garbrecht (2003) and Dalton et al. (2004) claimed that crop insurance programs in the US could benefit significantly from using seasonal climate forecasts. Applying

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decision optimization of the utility function, Cabrera et al. (2007) evaluated the most common insurance products for maize, cotton, and peanut in Florida under the uncertainty of future weather conditions. Also, Cabrera et al. (2006) developed a model to select the best crop insurance products within a whole-farm portfolio framework.

Another group of studies focused on identifying parameters for potential new crop insurance products. Among these studies Martin et al. (2001) linked an indemnity function with a rain forecast model to develop a precipitation insurance strategy for cotton farms in Mississippi. Vedenov and Barnett (2004) used weather derivatives to develop a new strategy for crop insurance instruments. Using random strike prices, Turvey et al. (2006) developed a pricing method for weather insurance for the Ontario ice-wine harvest.

From the insurer's point of view, Ker and McGowan (2000) presented a different approach that considers adverse selection of crop insurance according to ENSO phases. In this model, Ker and McGowan optimized the final pay off to the insurance agency rather to the farmers. Similarly, Turvey et al. (1999) portrayed a model that evaluated insurers' risk and developed an approach to computing actuarial reinsurance premiums. Previously, Abbaspour (1994) implemented a Bayesian risk methodology to help crop insurers cope with uncertainty and risk.

Few reports describe studies of farmer/insurer interactions and none of them have formally included climate information in their analysis. Wang and Zhang (2003) contrasted farmer and insurer perspectives to evaluate the feasibility of non-subsidized, private crop insurance and Menrad and Hirzinger (2005) compared the impacts of crop insurance for insurers and farmers as affected by cultivation of genetically modified plants.

Most empirical studies dealing with climate variation and crop insurance have unidirectional analyzed this issue, either from the farmers' or the insurers' perspective; and when interaction has been evaluated, climate has not been included into the analysis. In this paper we propose a more comprehensive analysis by contrasting both viewpoints in the assessment of an optimal crop insurance selection process under the influence of climate variability.

Several studies have shown that El Niño Southern Oscillation (ENSO) is a strong driver of seasonal climate variability that impacts cotton and peanut crop yields in the Southeastern US (e.g., Hansen, 2002; Jones et al., 2000). Moreover, recent advances in climate forecasting and the consequent ability to predict climate fluctuations provide opportunities to improve the management of climate-associated risks in agriculture. Thus, the Southeastern US offers an illustrative setting for studying the interaction of climate variability and crop insurance strategies.

The objective of this study is to assess optimal crop insurance strategies for farmers and insures based on different climatic scenarios and levels of risk aversion. Our hypothesis is that both conflicts and synergies exist between farmers and insurers regarding crop insurance selection, and these conflicts and synergies are influenced by climate variability. We took an empirical case study approach to identify a specific context for climate information in agricultural decision making in order to obtain a more accurate view of the users' decision process. As Yin (1994, p. 13) argues, case study is especially useful as an empirical method when the boundaries between the phenomenon and context are not clear. Earlier findings suggest that the fundamental structure of decisions based on a climate forecast cannot be divorced from their local content, which implies that the estimated economic value of a climate forecast loses meaning if separated from its context (Cabrera et al., 2007; 2006; Letson et al., 2005; Podestá et al., 2002).

CASE STUDY AND DATA

Peanut (*Arachis hypogaea* L.) and cotton (*Gossypium hirsutum* L.) are two of the most widely cultivated agronomic crops in the southeastern USA. A significant portion of these crops is grown under rainfed conditions making them extremely sensitive to climate variation and, thus, ideal for our study. In order to analyze the optimal selection of crop insurance products under climatic uncertainty, we used a 40-ha (100-acre) rainfed farm in Jackson County, FL that grows 50% peanut and 50% cotton on a *Dothan Loamy Sand* soil. This farm was selected taking into account similarities in environment, resources, and technology to other major agricultural production areas in the southeastern USA so our findings can be used as reliable proxies for a broader agricultural region.

Several authors including Hansen (2002), Mavromatis et al. (2002), and Jones et al. (2000) have reported the effect of climate variability due to ENSO on crop yields in Florida. The ENSO is characterized by changes in the sea surface temperature of the Equatorial Pacific Ocean that influences global climates, particularly that of the southeast USA. Rainfall in Florida is especially sensitive to ENSO phases (i.e., El Niño, La Niña, and Neutral) with a probability of above average rainfall about 40% during an El Niño year and a probability of below average rainfall about 30% during a La Niña year. Temperature is also affected by ENSO. Lower temperatures, especially before the planting season, are likely to be observed during El Niño and higher temperatures during La Niña (Jagtap et al., 2002).

Crop yields depend on several factors including technology, resources, planting dates, and weather conditions during the growing period. Therefore, predictability of seasonal climate variability, gives the opportunity to forecast probable crop yields for different planting scenarios. In this study, crop yields for peanut and cotton were simulated using a suite of biophysical simulation models (DSSAT v4.0, Jones et al., 2003) and daily weather records that were classified by ENSO phase (JMA, 1991). Inputs for the simulation model followed the current management practices of variety, fertilization and planting dates in the region following Boote et al. (1998) for peanut and Messina et al. (2003) for cotton.

The climate data, which included 65 years (1939-2003) of daily rainfall, maximum and minimum temperatures, and solar radiation, were obtained from the weather station at Chipley, FL. The limited duration of daily weather records provided relatively few realizations of each ENSO phase that we could use to assess their impacts on crop yields (14 for El Niño, 16 for La Niña, and 35 for Neutral years). To obtain more robust results we expanded the simulated data using a stochastic yield generator described by Cabrera et al. (2006). The final crop yield records were based on 990 cases for each ENSO phase, thus, there are 2,970 records for all years.

Table 1 presents a summary of the synthetically generated crops yields by ENSO phases and planting dates contrasted with their historical records. It is important to indicate that the simulated yields are consistent with previous research in Florida (e.g., Cabrera et al., 2007; Mavromatis et al., 2002; Hansen et al., 1998) and with historical data (NASS, 2007).

To simulate the necessary farm income series, synthetic prices series were generated according to Letson et al. (2005), with the following steps. First, monthly average prices received by Florida farmers for peanut and cotton were obtained from the USDA National Agricultural Statistics Service. Prices of cotton were increased by 18.7% to account for the seed value not included in the USDA statistics. The price series, which included data from January 1996 to January 2005, were deflated to January 2005 dollars using the US Consumer Price Index. In addition, these data were de-trended for seasonal differences by estimating monthly residuals with respect to their means. Principal component analysis was used to decompose the matrix of price residuals into three uncorrelated time series of amplitudes that were separately sampled. Sampled values were combined and back transformed to reconstruct crop price residuals. Kolgomorov-Smirnov tests confirmed that the correlation structure of synthetic price residuals was similar to that of the historical data and that the historical price distributions were well reproduced according to quantile-quantile plots. Finally, seasonal price averages for the harvesting periods of the two crops were re-introduced: 2 Sep - 6 Nov for peanut and 22 Sep - 28 Dec for cotton. Price distributions obtained with this method do not represent historical values, but rather distributions consistent with historical variability.

Table 1. Peanut and cotton synthetically generated and observed historical yields by ENSO phase. There were 2970 synthetic yields for all years and 990 synthetic yields for each ENSO phase. There were 65 years for all observed historical yields, 14 years for El Niño, 35 years for Neutral, and 16 years for La Niña.

Crop		All years		El Niño		Neutral		La Niña	
Variety		Mean	SD	Mean	SD	Mean	SD	Mean	SD
		- kg ha^{-1} -							
Peanut	Synthetic	3241	1294	3222	1283	3247	1356	3253	1216
Georgia Green	Observed[a]	3155	1311	3103	1302	3161	1361	3170	1262
Cotton	Synthetic	716	80	706	76	731	76	713	82
DP 555	Observed	703	83	693	79	724	80	701	85

[a] Observed historical yields are from NASS (2007).

Variable and fixed costs of production and labor requirements for contemporary practices in the region were incorporated deterministically in the model. Data for the two crops were provided by the North Florida Research and Education Center in Quincy, FL. Annual variable costs were \$1,088 ha^{-1} for peanut and \$1,122 ha^{-1} for cotton. Fixed costs were \$344 ha^{-1} for peanut and \$177 ha^{-1} for cotton.

To provide more realistic farm scenarios and to reduce the number of decisions in our model, only the most common insurance products used by farmers in the Jackson County were included in the analysis. Specifically, the studied crop insurance products for peanut and cotton were: CAT or Catastrophic coverage; and, 65, 70, and 75% Actual Production History (APH; also called Multi-Peril Crop Insurance). Additionally, 65, 70, 75, 80, 85% Crop Revenue Coverage (CRC) were included for cotton. The farmer's choice of no insurance selection was also included. In this study we diverge from Cabrera et al. (2006) in which the premiums received by the insurer included both government subsidies and premiums. Premiums were computed using the *Premium Calculator* at the USDA Risk Management Agency Website [http://www3.rma.usda.gov/apps/premcalc/], though these calculations might change in response to farm policy changes.

METHODS

A stochastic non-linear whole-farm model was implemented to select optimal crop insurance combinations according to ENSO phase and risk aversion level. However, the implemented model differed between farmer and insurer to account for their specific business goals. The farmer's case was evaluated by maximizing a constant relative risk aversion utility function (Cabrera et al., 2006); whereas, the insurer's optimal choices were computed using a minimization of losses framework constrained by a conditional value-at-risk model (CVaR) (Liu et al., 2006). These techniques are discussed in the following subsections.

OPTIMAL FARM DECISIONS FOR THE FARMER

To evaluate the impact of climate information on the farm decision making process and to estimate the value of crop insurance choices on farm net returns, we implemented a stochastic non-linear whole-farm model. This mathematical programming model was systematically solved to identify optimal planting dates and to simulate annual net returns based on the chance of forecasting a given phase for ENSO, available crop insurance products, and different levels of risk aversion. We assume that climate conditions and crop prices are unknown at the decision time but that their historical distributions are known. The model maximized the expected utility (***U***) at the end of one-year planning horizon using the following objective function:

$$Max\, E[U(W_f)] = \sum_{n=1}^{N} U(W_0 + \Pi_{i,n})/N, \qquad \text{for } n = 1 \text{ to N}; i = 1, 2, 3, 4 \qquad [1]$$

where:

$$U(W_f) = \frac{W_f^{1-R_r}}{1-R_r}, \qquad \text{for } R_r = 0, 1, 2, 3, 4 \qquad [2]$$

$$\Pi_{i,n} = \sum_{j=1}^{2} Y_j P_j X_j + IY_j PB_j X_j - C_j X_j - \mathrm{Pr}_j X_j, \qquad [3]$$

subject to:

$$\sum_{m=1}^{9} X_{m,j} = 0.5, \sum_{m=10}^{13} X_{m,j} = 0.5, \; X_m \geq 0 \qquad \text{for } j = 1; \text{ for } j = 2 \qquad [4]$$

where: ***i*** = ENSO phase (1 = El Niño, 2 = Neutral, 3 = La Niña, 4 = all years);
j = crop (1 = peanut, 2 = cotton);
m = planting date (1 to 9 for peanut: 16, 23 April, 1, 8, 15, 22, 29 May, 5, 12 June) (10 to 13 for cotton: 16, 23 April, 1, 8 May);
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);
R_r = constant risk aversion coefficient;
Π = net returns;
W_0 = initial wealth;
W_f = final wealth;
Y = crop yield;
IY = indemnity yield for insurance purposes (i.e., the compensation a farmer receives to cover losses below insured yield levels);
P = crop price;
PB = price base for insurance purposes;
C = production cost;
Pr = insurance premium; and,
X = percentage of land allocation for every crop planting date.

We assessed the riskiness of the decision strategies by allowing the utility to be a power function of wealth, based on a constant relative risk aversion coefficient (Equation 2). Based on Hardaker et al. (2004) we considered five possible risk aversion levels: $R_r = 0$ or risk neutrality; $R_r = 1$ or normal aversion; $R_r = 2$ or rather averse; $R_r = 3$ or very averse; and $R_r = 4$ or almost paranoid.

OPTIMAL FARM DECISIONS FOR THE INSURER

The insurer's case was also analyzed using a stochastic non-linear whole-farm model. In this case, the model was systematically solved to identify optimal planting dates to yield annual insurer minimum losses for all combinations of ENSO phases and available crop insurance products. The model assumed the farmer selects some type of insurance contract for each cultivated crop with half of the land devoted to each crop. This procedure was repeated for each combination of peanut and cotton crop insurance product. The model minimized losses (***L***) for one-year planning horizon, using the following function:

$$\underset{x}{Min}\, E[L] = \sum_{n=1}^{N}\sum_{j=1}^{2} X_{m,i,j} IY_{i,j} PB_{i,j} - X_{m,i,j} \Pr_{i,j} / N \,, \qquad \text{for } i\text{=1 to 4; m=1 to 13} \qquad [5]$$

subject to:

$$\sum_{m=1}^{9} X_{m,j} = 0.5\,, \sum_{m=10}^{13} X_{m,j} = 0.5\,, X_m \geq 0 \qquad \text{for } j\text{=1; for } j\text{=2} \qquad [6]$$

$$CVaR_{\alpha}[L(\vec{x},\vec{\xi})] \leq v \qquad [7]$$

where: $\vec{x} = \{X_m, \lambda_j\}$ is the decision vector,

$\vec{\xi} = \{Y_j, P_j\}$ is the random vector,

λ_j = selection of insurance policy for crop j.

To manage the insurer's risk levels within this framework we implemented a CVaR model (Rockafellar and Uryasev, 2002), which includes different risk levels to control for climate uncertainty as well as uncertainty related to honesty or moral hazard. CVaR is a financial adaptation of the chance-constrained programming for stochastic optimization models (Prekopa, 1995; Charnes and Cooper, 1959) developed to hedging a portfolio of financial instruments (crop insurances in our case) to reduce risk. The objective to minimize loss returns (L) is constrained under a CVaR (Equation 7), so the insurer can control the risk (α) associated with a combination of insurance contracts so that losses are no greater than a defined threshold (v). A detailed mathematical derivation of the CVaR model in agriculture can be found in Rockefellar and Uryasev (2002).

Optimization models for both farmers and insurers were solved using the MINOS5 algorithm in GAMS (Gill et al., 2000) along with a randomized procedure to alter starting values and assure global maxima solutions. Optimum values were then binned by ENSO phase and risk aversion level and then ranked to select the best performing crop insurance combination.

INSURANCE LOSS RATIO

We used the insurance loss ratio index to further analyze the potential synergies and conflicts between farmers and insures. In general terms, a loss ratio corresponds to what an insurer spends to pay the claims of its customers, expressed as a proportion of its premium. The loss ratio is a fair measure of the value of an insurance product from a consumer perspective (Rupp, 1991). This index can be used to evaluate conflicts and synergies between farmer and insurer by depicting how much of the premium received by the insurer is collected as indemnity by the farmer. The loss ratio (***LR***) can be calculated by dividing the indemnity by the premium:

$$LR_{i,n} = \sum_{j=1}^{2} (IY_j PB_j X_j)/(\Pr_j X_j) \qquad [8]$$

The Federal Crop Insurance Corporation (FCIC) in 2005 targeted an overall acceptable loss ratio of 1.075. That is, in the long-run crop insurance companies should be willing to pay out7.5% more than the premiums they receive. We calculated and evaluated the loss ratio of all different insurance contracts with respect to how much of the premium the insurer returns as indemnity to the farmer and how much proportion of the records, in a determined contract, would reach a targeted loss ratio between 1.000 (all premium is returned as indemnity) and 1.075 (FCIC targeted loss ratio).

RESULTS AND DISCUSSION

FARMER'S BEST PERFORMING CROP INSURANCE COMBINATIONS

Table 2 presents the farmer's best performing crop insurance combinations under different risk aversion levels and scenarios for ENSO phases. These crop insurance combinations were selected based on the estimated farm net returns for a 1-year planning horizon. Outcomes reported here represent the average net returns for farmers and insurers based on uncertain climate and prices, but it is important to recognize that these results are probabilistic distributions that include all potential combinations of climate and prices by ENSO phase. As expected, the yearly average predicted returns decreased with increased risk aversion levels. In addition, a comparison of farm net returns between the ENSO phases and 'all years' shows that the latter has statistically smaller average net returns than the ENSO phases based on independent Student's t-test. Smaller returns for 'all years' would be expected because this group did not include climate forecasts information in its farm decisions framework. The net returns difference between any ENSO phase and 'all years' could be considered as the added value of using climatic information.

Results show that higher returns were simulated for low or no insurance coverage for cotton combined with high coverage for peanut independent of ENSO phase. The highest net returns were obtained during El Niño years with the no insurance option for cotton and 75% APH for peanut (average=$18,265/year and $CI_{(95\%)}$=[17,027-19,502]). The lowest return 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 $CI_{(95\%)}$=[11,741-14,154]).

As indicated above, differences were also found depending on the farmer's risk aversion level. For low risk aversion level (R_r = 0 and 1), the optimization analysis showed the same best crop insurance combinations across ENSO phases. The analysis suggests that under risk aversion neutral (R_r = 0) and normal (R_r = 1) the best crop insurance combination are no coverage or CAT coverage for cotton and 65 to 75% APH for peanut.

Table 2. Optimal cotton and peanut crop insurance combinations for farmers according to average net returns by ENSO phase and level of risk aversion.

Risk aversion	All years		El Niño		Neutral		La Niña	
	Insurance[a]	Average returns[b]	Insurance	Average returns	Insurance	Average returns	Insurance	Average returns
0 Neutral	No Ins 75% APH	$17,065	No Ins 75% APH	$18,265	No Ins 75% APH	$17,641	No Ins 75% APH	$18,022
1 Normal	No Ins 75% APH	$16,519	No Ins 75% APH	$17,561	No Ins 75% APH	$17,085	No Ins 75% APH	$17,346
2 Rather	No Ins No Ins	$14,506	CAT 65% APH	$15,553	CAT 70% APH	$15,543	No Ins 70% APH	$15,086
3 Very	No Ins No Ins	$13,780	CAT 65% APH	$14,905	CAT 70% APH	$14,768	No Ins 70% APH	$14,452
4 Extreme	No Ins No Ins	$13,107	CAT 65% APH	$14,276	CAT 70% APH	$14,016	No Ins 70% APH	$13,832

[a] Crop insurance combinations are for cotton (top) and peanut (bottom); CRC = crop revenue coverage; APH = actual production history; CAT = catastrophic coverage; and No Ins = no insurance.
[b] Average net returns are in 2005 dollars ha^{-1}.

For higher risk aversion levels (R_r = 2, 3 and 4) the crop insurance combinations differed across ENSO phases and risk aversion levels. For cotton, no insurance and CAT coverage were maintained as the best insurance combination. For peanut, however, lower coverage levels were selected. For the case of 'all years,' no insurance for both crops resulted in the highest net income.

Crop insurance coverage is just one way that farmers can reduce exposure to risk. Peanut is fairly resistant to changes in the extremes of its yield variability and major impacts on production from 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 not necessarily by buying more crop insurance. The trade off is increased financial risk versus reduced production risk. The risk-averse farmer would find for the case of peanut that the cost of insurance premium is not worth the additional protection provided by the insurance.

INSURER'S BEST PERFORMING CROP INSURANCE COMBINATIONS

The optimal insurance combinations for minimum losses for the insurer were transformed to maximum gains by applying duality. Optimization analysis for the insurer shows average gains ranging from $23 to $258 ha year^{-1}. Minimum gain occurred for a contract CAT for cotton and 70% APH for peanut for La Niña and El Niño years, compared with CAT for cotton and peanut for Neutral years. Maximum gain occurred for 85% CRC for cotton and 75% APH for peanut for La Niña and Neutral years, whereas 85% CRC for cotton and 65% APH for peanut gave the maximum gain for El Niño years. Figure 1 summarizes the average gains by insurance contracts and ENSO phase. Lines cross over in several points indicating different climate impacts by insurance contract.

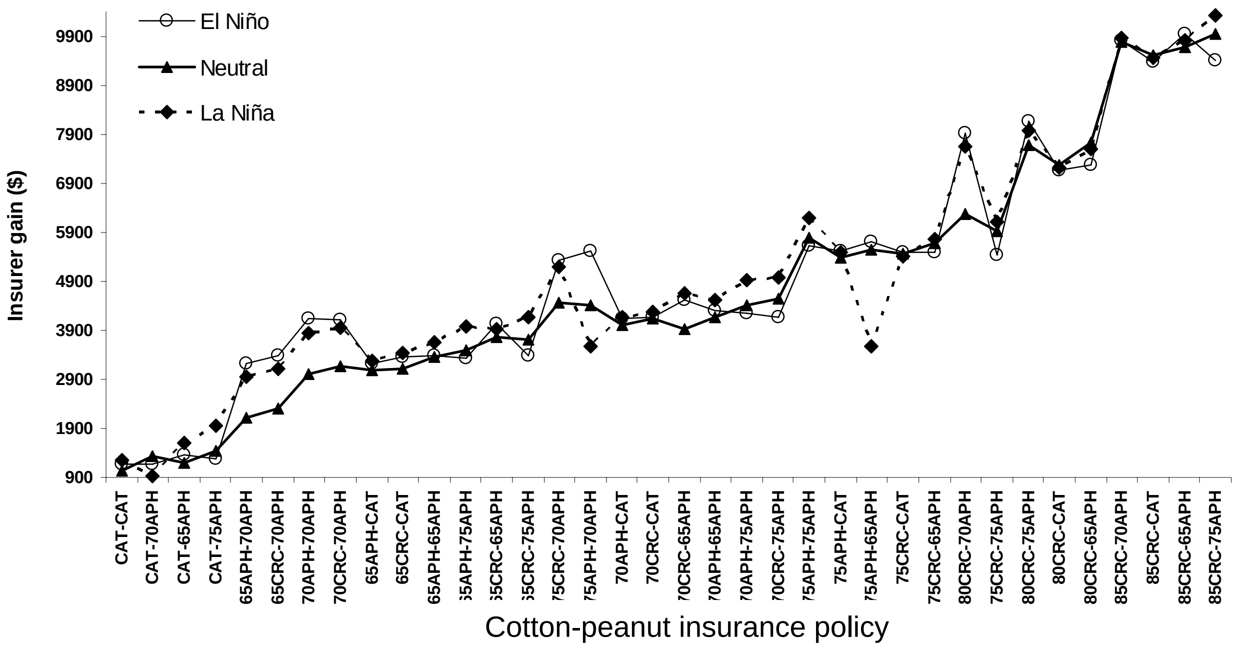

Figure 1. Average gain of insurer per crop insurance contract and ENSO phase

Table 3 shows the optimum crop insurance contracts that 90, 95, or 99% of the time (risk level) have higher returns than a specific threshold (risk value). The contract 85% CRC-65% APH was the best combination for El Niño years. However, if the insurer wants to obtain returns higher than \$4,000 (or \$100 ha^{-1}) 95% of the time, 75% APH-CAT would be the best contract. Likewise, the best contract for El Niño years to have 99% of the time higher than \$2,000 (or \$50 ha^{-1}) would be 75% APH-CAT. There was no contract available that 99% of the time had a gain greater than \$4,000.

SYNERGIES AND CONFLICTS BETWEEN FARMER AND INSURER

Figure 2 combines the farmer and the insurer net returns, both expressed as percentages of their maximums, by ENSO phase and crop insurance contract. As expected, conflicts of interest are found at the extremes of the graphs presented in Figure 2. Maximum gains for farmers (insurers) imply minimum gains for insurers (farmers). The contract 85% CRC-CAT was the lowest net return generator for the farmer while it brought one of the greatest gains to the insurer. Likewise, contracts such as CAT-75% APH for El Niño and Neutral and CAT-70% APH for La Niña had the greatest net returns for the farmer with the lowest gains for the insurer.

However, Figure 2 also depicts synergies between insurer and farmer. Synergies can be found in areas where percentages of insurer gain and farmer net return are alike. Considering the 40 to 60% interval a reasonable range where insurer and farmer would converge in their interests, it is possible to find some synergic crop insurance alternatives. Specifically, the synergic crop insurances are: 75% APH-75% APH and 75% CRC-CAT for all ENSO phases; in addition, 75% APH-CAT for Neutral and La Niña; 75% APH-70% APH for El Niño; and 80% CRC-70% APH and 75% APH-65% APH for Neutral. Neutral years had five synergetic contracts, whereas El Niño and La Niña only had three.

Table 3. Best crop insurance contract for insurers according to risk values and risk levels

		Risk Level		
	Risk Value	90%	95%	99%
El Niño	<-4000	85% CRC-65% APH	85% CRC-65% APH	85% CRC-65% APH
	-4000-2000	85% CRC-65% APH	85% CRC-65% APH	85% CRC-65% APH
	-2000-0	85% CRC-65% APH	85% CRC-65% APH	85% CRC-65% APH
	0-2000	85% CRC-65% APH	85% CRC-65% APH	85% CRC-65% APH
	2000-4000	85% CRC-65% APH	85% CRC-65% APH	75% APH-CAT
	>4000	85% CRC-65% APH	75% APH-CAT	NA†
Neutral	<-4000	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	-4000-2000	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	-2000-0	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	0-2000	85% CRC-75% APH	85% CRC-75% APH	65% APH-CAT
	2000-4000	85% CRC-75% APH	85% CRC-75% APH	75% APH-CAT
	>4000	85% CRC-75% APH	75% APH-CAT	NA
La Niña	<-4000	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	-4000-2000	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	-2000-0	85% CRC-75% APH	85% CRC-75% APH	85% CRC-CAT
	0-2000	85% CRC-75% APH	85% CRC-75% APH	70% APH-CAT
	2000-4000	85% CRC-75% APH	85% CRC-75% APH	75% APH-CAT
	>4000	85% CRC-CAT	85% CRC-CAT	NA
All years	<-4000	85% CRC-75% APH	85% CRC-75% APH	85% CRC-75% APH
	-4000-2000	85% CRC-75% APH	85% CRC-75% APH	75% APH-65% APH
	-2000-0	85% CRC-75% APH	85% CRC-75% APH	65% APH-CAT
	0-2000	85% CRC-75% APH	85% CRC-75% APH	75% APH-CAT
	2000-4000	85% CRC-75% APH	85% CRC-CAT	NA
	>4000	85% CRC-CAT	NA	NA

NA = No insurance available.

INSURER LOSS RATIOS BY OPTIMAL CROP INSURANCE CONTRACTS

It is important to indicate that farmers and insurers are not antagonists in the farm insurance market. Without farmers, insurers have no business; and without insurers, farming becomes extremely risky. However, one factor that may be inducing conflicts between farmers and insures could be an overpriced insurance premium (i.e., the price of the insurance premium is higher than its long-run expected benefits).

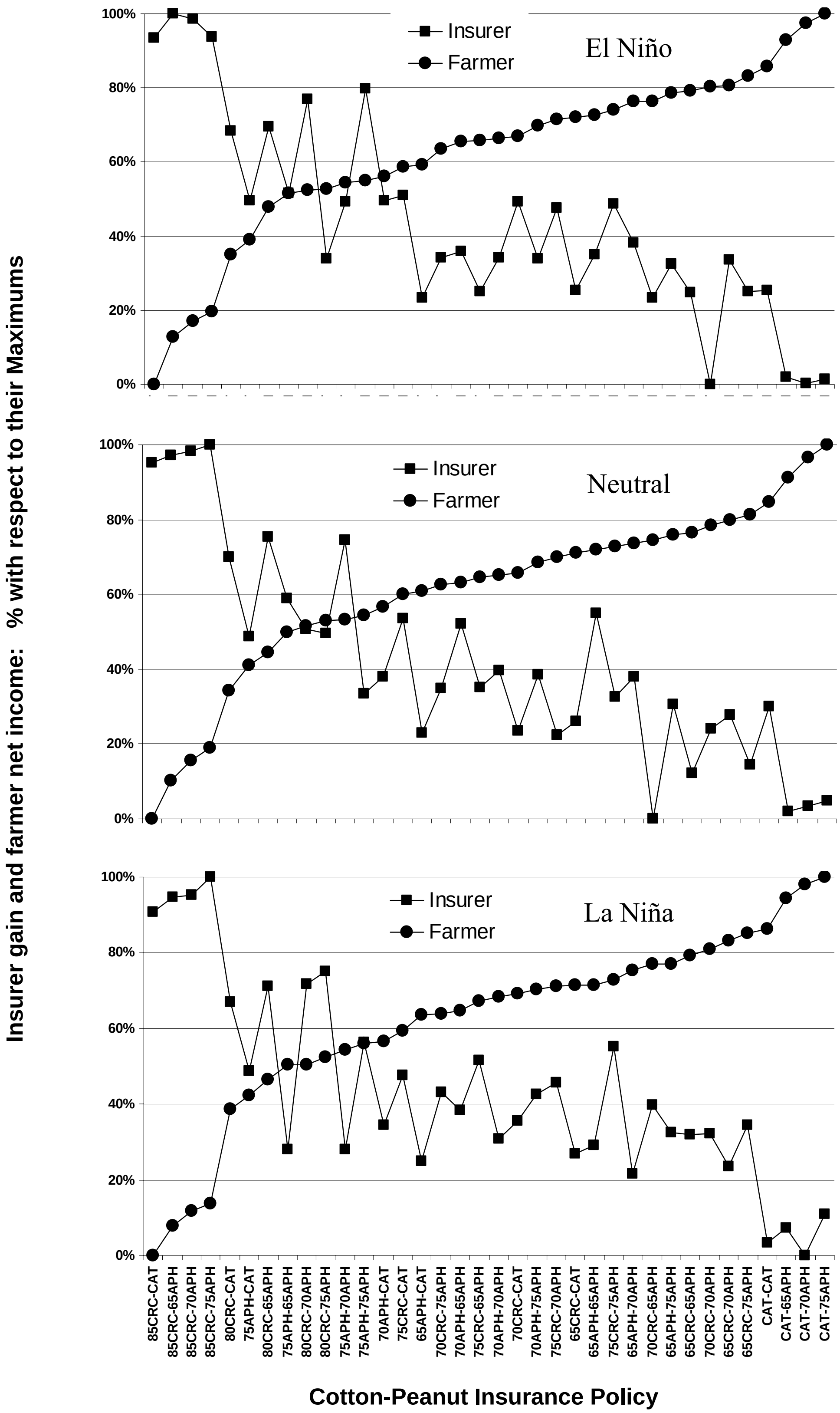

Figure 2. Insurer gain and farmer net income expressed by percentage of their maximums by crop insurance contract and ENSO phase.

To evaluate this issue, we compute the insurer loss ratio for all optimal crop insurance contracts presented earlier. The empirical results show that the average loss ratio for all years was 0.32, indicating that only 32% of the premium received was used to pay indemnities. The average insurer's loss ratios currently reported by the Federal Crop Insurance Corporation for Florida are 0.64 for peanuts and 0.36 for cotton. This ratio decreased when using climate information to 0.27 for El Niño, 0.30 for Neutral, and 0.26 for La Niña suggesting that the value of the climatic information has a greater significance for insurers than for farmers. Figure 3 shows the average loss ratio by insurance contract and ENSO phase. The lowest loss ratios occurred for 65, 70, and 75% APH for cotton and CAT for peanut contracts during La Niña; and 75% APH-CAT contracts during El Niño and Neutral. The greatest loss ratios occurred for CAT-75% APH for El Niño, 65% CRC-70% APH for Neutral, and CAT-70% APH during La Niña.

The results presented above are far from a 1.075 long-run loss ratio targeted by the Federal Crop Insurance Corporation (FCIC) in 2005. Local insurer's loss ratios reported in this paper consider only two crops in one county and are not intended for evaluating the whole US insurance market. No insurance contract reached on average a loss ratio between 1 (indemnity is equal to premium) and 1.075 (7.5% beyond premium loss). However, Figure 4 shows that most of the contracts had a number of realizations that reached such a range of target loss ratio. There was great variability in such frequency influenced primary by climate variability. Depending on ENSO phase, the frequency varied from zero (75% APH-75% APH and 80% CRC-CAT contracts) to 65 in Neutral years (65% CRC-75% APH), to 54 in El Niño years (75% CRC-75% APH), and to 43 in La Niña years (65% CRC-65% APH).

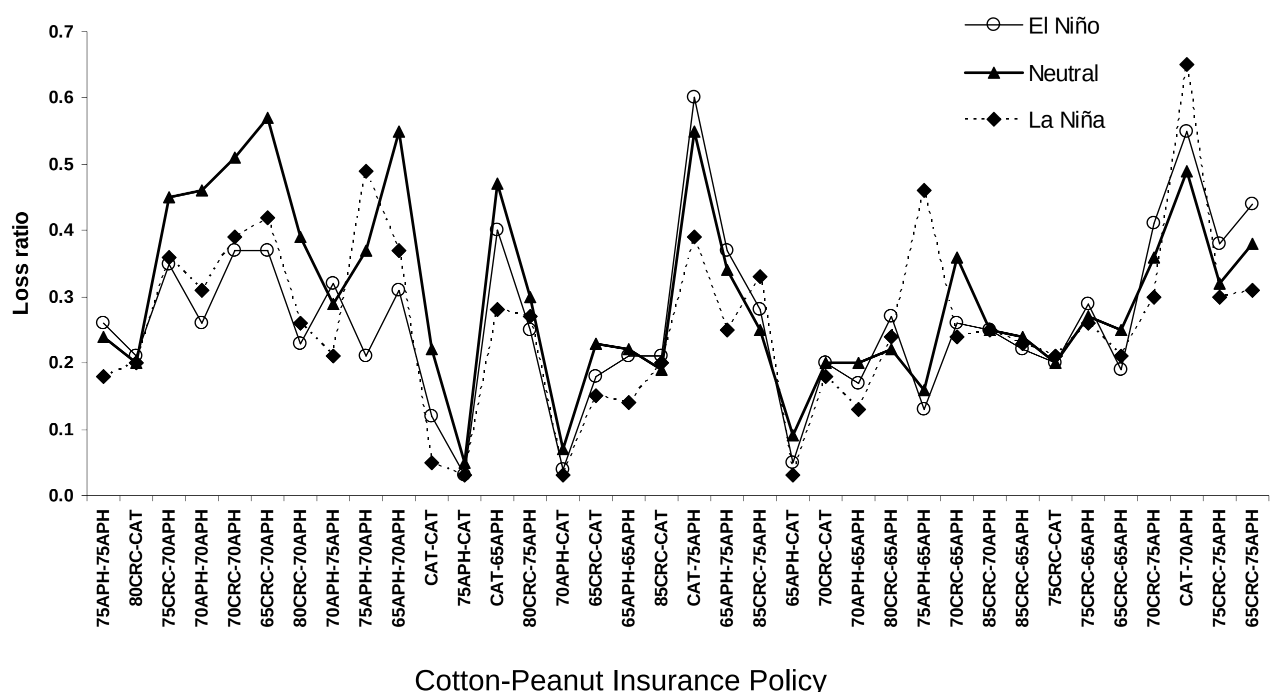

Figure 3. Average loss ratio for different crop insurance contract combinations and ENSO phases.

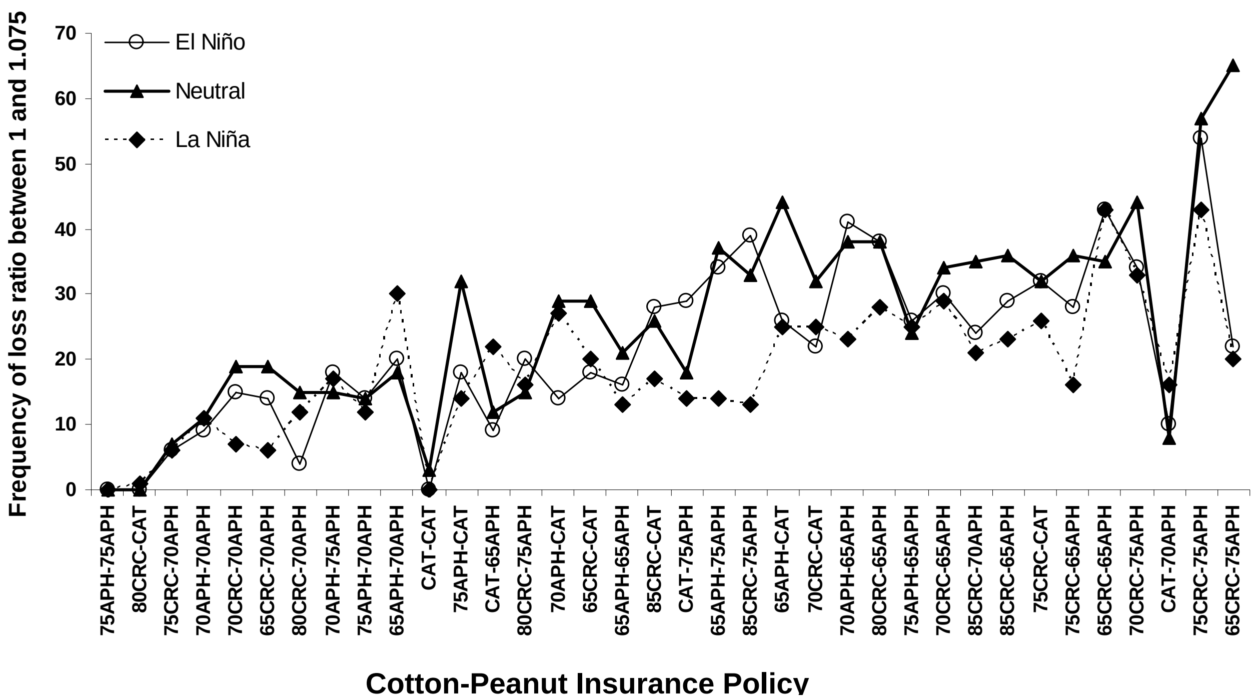

Figure 4. Frequency with which the loss ratio was between 1 and 1.075 for different crop insurance combinations and ENSO phases.

Climate variability had great impact on the farmer net return and insurer gain, impacting also the overall loss ratio and the probability to reach a target loss ratio. This climatic impact was noticed be the highest for the 65% CRC-75% APH contract that had 41% higher (Neutral) and 55% lower (El Niño and La Niña) probabilities of being in the range target loss ration than 'all years'. Insurance policies within the FCIC targeted loss ratio may increase the range of synergic crop insurance alternatives improving expected farmers' returns. This is an area that merits further research.

CONCLUSIONS

This study analyzed the potential synergies and conflicts of interest between farmers and insurers in the selection of an optimal crop insurance contract in the presence of climate variability. Our results show that our representative farmer's net returns is significantly affected by the crop insurance policy purchased and the risk aversion level selected. Long-run gains for insurers are directly related to the premium received and risk levels. In addition, year-to-year, ENSO-based climate variability affected farmer returns and insurer gains according to crop insurance contracts.

Whereas we did find evidence of conflicting interests between insurers and farmers regarding crop insurance selection, their best choices are seldom contradictory. So, if both parties are willing to show flexibility regarding their best selections, farmers and insurers can both attain long term sustainability without jeopardizing their economic stability. However, only the insurer has the capacity to change the underwritten crop insurance policy contracts under the commitment to help farmers attain economic stability. Therefore, the insurer would have a greater ability to resolve these conflicts of interests. Using ENSO-based climate forecast would be a critical factor on this decision selection process.

Another important outcome is that average loss ratio found for insures was 0.32; that is, only 32% of the premium received was used to pay indemnities. This ratio is significantly lower than a 1.075 long-run loss ratio that was targeted by policy makers; suggesting that for the region and crops considered significant room would exist for decreasing farmers' premium, while still attaining economically feasible loss ratio targets.

In sum, the results of this study agree with the spirit of Changnon et al. (1999) who suggest that climate information can help farmers and insurers to mitigate losses related to climate variability. Climate information can help farmers to select a better planting window and to establish production strategies that include crop insurance that maximize their net returns. In addition, this kind of information may assist insurers to assess risks more precisely. Thus, insurers and farmers can bridge their divergent interests by improving their understanding of the effect of climate conditions on the development of sustainable business plans.

Although this study has focused on presenting an analysis with great farm-level detail and a large temporal data distribution, the spatial dimension was omitted. Consequently, studying the value of location on the impact of climate and crop insurance on farm net returns could be an area for future refinement of the model implemented here.

REFERENCES

Abbaspour K. 1994. Bayesian risk methodology for crop insurance decisions. *Agricultural and Forest Meteorology* 71: 297-314.

Boote K, J Jones, G Hoogenboom. 1998. Simulation of crop growth: CROPGRO model. In *Agricultural Systems Modeling and Simulation,* R. Peart and R. Curry, eds. Marcel Dekker, New York, NY.

Cabrera VE, C Fraisse, D Letson, G Podestá, J Novak. 2006. Impact of climate information on reducing farm risk by optimizing crop insurance strategy. *Transactions of the American Society of Agricultural Engineers* 49: 1223-1233.

Cabrera VE, D Letson, G Podestá. 2007. The value of the climate information when farm programs matter. *Agricultural Systems* 93: 25-42.

Changnon S, E Fosse, E Lecomte. 1999. Interactions between the atmospheric sciences and insurers in the United States. *Climatic Change* 42: 51-67.

Charnes A, W Cooper. 1959. Chance-constrained programming. *Management Science* 6: 73-79.

Chen C, C Chang. 2005. The impact of weather on crop yield distribution in Taiwan: some new evidence from panel data models and implications for crop insurance. *Agricultural Economics* 33: 503-511.

Dalton T, G Porter, N Winslow. 2004. Risk management strategies in humid production regions: a comparison of supplemental irrigation and crop insurance. *Agricultural and Resource Economics Review* 33: 220-232.

Gill P, W Murray, B Murtagh, M Saunders, M Wright. 2000. *GAMS/MINOS in GAMS: Solver Manuals*. GAMS Development Corp., Washington, DC.

Hansen J. 2002. Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. *Agricultural Systems* 74: 309-330.

Hansen J, A Hodges, J Jones. 1998. ENSO influences in agriculture in the Southeastern US. *Journal of Climate* 11: 404-411.

Hardaker J, R Huirne, J Anderson, G Lien. 2004. *Coping with Risk in Agriculture*. 2nd edition. CABI Publishing

Hill H, J Mjelde. 2002. Challenges and opportunities provided by seasonal climate forecasts: a literature review. *Journal of Agricultural and Applied Economics* 34: 603-632.

Jagtap S, J Jones, P Hildebrand, D Letson, J O'Brien, G Podestá, D Zierden, F Zazueta. 2002. Responding to stakeholder's demands for climate information: from research to applications in Florida. *Agricultural Systems* 74: 415–430.

JMA (Japan Meteorological Agency). 1991. *Climate Charts of Sea-Surface Temperature of the Western North Pacific and the Global Ocean*. Marine Department, Japan Meteorological Agency, Tokyo, Japan.

Jones J, G Hoogenboom, C Porter, K Boote, W Batchelor, L Hunt, P Wilkens, U Singh, A Gijsman, J Ritchie. 2003. The DSSAT cropping system model. *European Journal of Agronomy* 18: 235−265.

Jones J, J Hansen, F Royce, C Messina. 2000. Potential benefits of climate forecasting to agriculture. *Agriculture, Ecosystems and Environment* 82: 169-184.

Ker A, P McGowan. 2000. Weather-based adverse selection and the U.S. crop insurance program: the private insurance company perspective. *Journal of Agricultural and Resource Economics* 25: 386-410.

Letson D, G Podestá, C Messina, A Ferreyra. 2005. The uncertain value of perfect ENSO phase forecasts: stochastic agricultural prices and intra-phase climatic variations. *Climatic Change* 69:163-196.

Liu J, C Men, VE Cabrera, S Uryasev, CW Fraisse. 2006. *CVaR* model for optimizing crop insurance under climate variability. University of Florida, ISE Dept. Res. Report 2006-1.

Mavromatis T, S Jagtap, J Jones. 2002. El Niño-Southern Oscillation effect on peanuts yield and N leaching. *Climate Research* 22: 129-140.

Mahul O. 2001. Optimal insurance against climatic experience. *American Journal of Agricultural Economics* 83: 593-604.

Martin S, B Barnett, K Coble. 2001. Development and pricing precipitation insurance. *Journal of Agricultural and Resource Economics* 26: 261-274.

Mendelsohn R, A Dinar, L Williams. 2006. The distributional impact of climate change on rich and poor countries. *Environment and Development Economics* 11: 159-178.

Menrad K, T Hirzinger. 2005. Impacts if the genetic modification plants on crop insurance schemes. *Berichte Uber Landwirtschaft* 83: 252-277.

Messina C, J Jones, C Fraisse. 2003. *Development of cotton CROPGRO Crop Model*. Southeast Climate Consortium, Staff Paper Series 05-05.

Mjelde J, H Hill. 1999. The effect of the use of improved climate forecasts on variable costs, input usage, and production. *Agricultural Systems* 60: 213-225.

Mjelde J, T Thompson, C Nixon. 1996. Government institutional effects on the value of seasonal climate forecasts. *American Journal of Agricultural Economics* 78: 175-188.

NASS (National Agricultural Statistics Service). 2007. Corn and Cotton production in Florida: 1939-2003. Washington, D.C.: USDA National Agricultural Statistics Service. Database available at: www.nass.usda.gov.

Podestá G, D Letson, C Messina, F Royce, R Ferreyra, J Jones, J Hansen, I Llovet, M Grondona, J O'Brien. 2002. Use of ENSO-related climate information in agricultural decision making in Argentina: a pilot experience. *Agricultural Systems* 74: 371-392.

Prekopa A. 1995. *Stochastic Programming*. Dordrecht: Kluwer Academic Publishers.

Rockafellar R, S Uryasev. 2002. Conditional value-at-risk for general loss distributions. *Journal of Banking and Finance* 26: 1443-1471.

Rupp R. 1991. *Rupp's Insurance and Risk Management Glossary*. Nils Pub Co.

Schneider J, J Garbrecht. 2003. A measure of usefulness of seasonal precipitation forecasts for agricultural applications. *Transactions of the American Society of Agricultural Engineers* 46: 257-267.

Turvey C, A Weersink, A Chiang. 2006. Pricing weather insurance with a random strike price: the Ontario ice-wine harvest. *American Journal of Agricultural Economics* 88: 696-709.

Turvey C, G Nayak, D Sparling. 1999. Reinsuring agricultural risk. *Canadian Journal of Agricultural Economics* 47: 281-291.

USTR (Office of the United States Trade Representative). 2006. *Repealing Cotton Subsidy Program, Press Release, February 2006*. Washington, DC.

Vedenov D, B Barnett. 2004. Efficiency of weather derivatives as primary crop insurance instruments. *Journal of Agricultural and Resource Economics* 29: 387-403.

Wang H, H Zhang. 2003. On the possibility of a private crop insurance market: a spatial statistics approach. *Journal of Risk and Insurance* 70: 111-124.

Yin R. 1994. *Case Study Research Design and Methods*. Sage Publishers, Thousand Oaks, CA.