Optimal Crop-Insurance Strategies under Climate Variability: Contrasting Insurer and Farmer Interests

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, OR, July 29-August 1, 2007

This work has been supported by NOAA (Climate Programs Office), USDA (Risk Management Agency) and USDA (Cooperative State Research, Education and Extension Service).

OPTIMAL CROP-INSURANCE STRATEGIES UNDER CLIMATE VARIABILITY: CONTRASTING INSURER AND FARMER INTERESTS

Víctor E. Cabrera, Daniel Solís and David Letson

Abstract: This study analyzes the potential synergies and conflicts of interest 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. To do so, we consider a representative 40 hectares, rainfed, cotton-peanut farm located in Jackson County in Florida. Our results show that year-to-year ENSO-based climate variability affects farmers' income and insurers' gains according to crop insurance contracts. Additionally, introduction of ENSO-based climate forecasts presents a significant impact on the selection of a particular contract. 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.

Key Words: Conflict of Interest, Crop Insurance, ENSO, Risk Management.

1. Introduction

Climatic variability significantly affects agricultural production, profitability and risk (Mendelsohn, Dinar and Williams, 2006; Chen and Chang, 2005). Predictability of seasonal climate variations can help in reducing farm risk by tailoring agricultural management strategies to mitigate the impacts of adverse conditions or to take advantage of favorable conditions (Letson et al., 2005; Mjelde, Thompson and Nixon, 1996). 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 economic stability under the uncertainty of future random events, including climate (Mahul, 2001). However, optimal crop insurance choices for farmers differ from those of insurers, who seek to minimize losses. In addition, once farmers buy crop insurance, they have a greater incentive to engage in risky behavior; clearly moral hazard can cause farmers' and insurers' interests to diverge. Predictable climate variations may offer an opportunity to close this gap.

Most empirical studies on climate and crop insurance focus on selecting the best insurance product for farmers (e.g., Cabrera et al., 2006; Leigh and Kuhnel, 2001; Mjelde, Thompson and Nixon, 1996); or have developed parameters for potential new crop insurance products (e.g., Turvey, Weersink, and Chiang, 2006; Martin, Barnett and Coble, 2001). Less frequently, researchers have taken the viewpoint of the insurer (e.g., Ker and McGowan, 2000). Few articles have explored the interaction between farmers and the insurer (e.g, Menrad and Hirzinger, 2005; Wang and Zhang, 2003), and none have formally included climate into the analysis. In consequence, the current study adds to the literature by offering a dual analysis of the crop insurance market in which both farmers' and insurers' viewpoints are used to select an optimal insurance product. Our hypothesis is that both conflicts and synergies exist between farmers and insurers regarding crop insurance selection and that they are influenced largely by climate variability.

To reach our goal we analyze the case of a representative 40 hectares (100 acres), rainfed, cotton-peanut farm located in Jackson County, Florida. The Southeastern U.S. offers an illustrative setting for studying the interaction of climate variability and crop insurance strategies. 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 this geographical area (e.g., Hansen, 2002; Jones et al., 2000). In this study we implement biophysical simulation models and a stochastic non-linear whole-farm optimization analysis to identify an optimum crop insurance product for farmers and insurers based on different scenarios for ENSO. The riskiness of the decision strategies is evaluated using a constant relative risk aversion utility function for farmers (Letson et al., 2005) and a conditional value-at-risk model for insurers (Rockafellar and

Uryasev, 2002). These results are then contrasted to evaluate the synergies and conflicts between the two groups under study.

The rest of this article is organized as follows. The next section gives an overview of the recent literature followed by a description of the farmer-insurer synergy-conflict model, the methodological framework and a description of the data used. Then, we discuss the empirical results and present some concluding remarks.

2. Literature Review

Crop insurance is a major component of risk management that farmers could use together with climate information to increase and stabilize their incomes. Crop insurance products have recently proliferated in the U.S. because of an increased interest in managing income risk by farmers, lenders and political leaders (Mahul, 2001; Mjelde, Thompson and Nixon, 1996). Farmers now 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. Additionally, premiums charged to farmers, which have historically included a fixed subsidy, now have a regressive proportional subsidy that overall is significantly greater. Consequently, there is a need to study the potential interactions of climate-based forecasts and crop insurance strategies on the stability of farm income.

As indicated, most empirical studies on this area of research 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, Thompson and Nixon (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 and sorghum using utility functions under uncertain weather forecasts. Schneider and Garbrecht (2003) and Dalton, Porter and Winslow (2004) claimed that crop insurance programs in the U.S. could benefit significantly from using seasonal climate forecasts information. Applying decision optimization of the utility function, Cabrera, Letson and Podestá (2007) evaluated the most common insurance products for maize, cotton and peanuts 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. In this study the authors evaluated all available crop insurance products for cotton and peanuts in Florida and related them with information on ENSO phases forecasting and different levels of risk aversion.

Another group of studies has focused on creating parameters for potential new crop insurance products. Along these studies Martin, Barnett and Coble (2001) linked an indemnity function with a rain forecast model to develop a precipitation insurance strategy for cotton farms in Mississippi. Using random strike prices, Turvey, Weersink and Chiang (2006) developed a pricing method for weather insurance for the Ontario ice-wine harvest. Ker and McGowan (2000) presented a different approach that deals with adverse selection of crop insurances according to ENSO phases. In this model Ker and McGowan optimized the final pay off with respect to the insurance agency rather to the farmers.

Also from the insurer's point of view, Turvey, Nayak and Sparling (1999) presented a model that evaluated insurers' risk and developed an approach to computing actuarial reinsurance premiums. Abbaspour (1994) presented a Bayesian risk methodology to help crop insurers cope with uncertainty and risk. Menrad and Hirzinger (2005) compared the impacts of crop insurance for insurers and farmers under the scheme of genetically modified plants. Lastly, Wang and Zhang (2003) contrasted farmer and insurer perspectives to evaluate the feasibility of nonsubsidized, private crop insurance. It is important to highlight that these last group of studies have not included climate information in their analysis.

In sum, most empirical studies dealing with climate variation and crop insurance have unidirectionally analyzed this issue, either from the farmers' or the insurers' perspective. 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. In the following section we conceptualize the farmer-insurer synergies-conflicts framework implemented in this article.

3. Conceptual Framework

In our synergy-conflict model the farmer and the insurer have different risk reduction strategies which are depicted in Figure 1. As shown by arrows **a**, **b**, **c**, and **d,** synergies and conflicts can be found depending on where farm income is located. Figure 1 shows all uncertain, but possible income levels that can take place before indemnities from crop insurance is applied. Farm income before insurance, which is defined as the crops net revenues less the share cost of the insurance premium, can be positive (more than expected), zero (expected), or negative (less that expected). Conversely, farm income after insurance includes indemnity payments when the farm income falls below the protected threshold. Thus, in this model there are three possible income zones for the farmers (i.e., gain, loss, and maximum loss) and another three zones for the insurer (maximum gain, gain, and loss).[1]

[FIGURE 1]

For instance, if farm income before insurance is positive (i.e., **a** falls inside the farmer's gain and the insurer's 'maximum gain' area), the situation is of mutual benefit for both the farmer and the insurer after insurance (synergy). In this case, the farmer has benefited from the production, and the insurer has accomplished the maximum gain. The insurer keeps the received premium (which includes farmer payments and government subsidies) since s/he does not pay any indemnities.

If farm income before insurance is negative but higher than the protected income (i.e., **b** falls inside the farmer's 'loss' and the insurer's 'maximum gain' area), the situation is of an economic loss for the farmer but still a maximum gain for the insurer after insurance (conflict). In this area, income is not protected, so the farmer does not receive insurance indemnities, and the insurer, as in the previous case, keeps the premium.

Arrows **a** and **b** represent maximum gains for the insurer but uncertain situations of gain or loss for the farmer.

On the other hand, if farm income before insurance is negative and lower than the protected income, but higher than the value of the premium received by the insurer (i.e., **c** falls inside the farmer's 'maximum loss' and the insurer's 'gain' area), the situation is of maximum possible loss for the farmer and of less gain than the premium for the insurer after insurance (conflict). In this area, farm income is protected for the crop insurance contracts, thus the insurer pays indemnities to the farmer to reach the farm income insured level. These indemnities however have less value than the premium the insurer received.

Lastly, if farm income before insurance is negative and lower than the value of the premium received by the insurer (i.e., **d** falls inside the farmer's 'maximum loss' and the insurer's 'loss' area), the situation is of maximum loss for the farmer and also of loss for the insurer (conflict). The insurer has to pay a higher value than the received premium as indemnities for the farmer to reach the protected level.

Therefore, arrows **c** and **d** represent indifferent situations of maximum loss for the farmer and uncertain situations of gain or loss for the insurer.

Hence, income risk strategies are different (though not opposite) for the farmer and the insurer. The farmer would seek to maximize gains, while the insurer would seek to minimize losses. In this study we evaluate these synergies and/or conflicts of interest by comparing relative proportions of farmer's maximum gains versus insurer's minimum losses for a crop insurance contract under determined ENSO phase and level of risk aversion. We also evaluated these synergies and conflicts of interest by calculating loss ratios, which are the indemnity payments from the insurer to the farmer expressed as proportion of premium.

4. Case Study and Data

A 40 hectares (100 acres) rainfed farm in Jackson County in Florida that grows 50% peanut (*Arachis hypogaea* L.) and 50% cotton (*Gossypium hirsutum* L.) in soil type *Dothan Loamy Sand* was used as a case study. This farm was designed taking into account similarities in environment, resources and technology to other major agricultural production areas in the Southeastern U.S. Thus, our findings can be used as reliable proxies for a broader agricultural region.

Several authors including Hansen (2002), Mavromatis, Jagtap and Jones (2002) and Jones et al. (2000) have reported the effect of climate variability due to ENSO on crop yields in Florida. ENSO is a climatic phenomenon characterized by changes in the sea surface temperature of the Equatorial Pacific Ocean that influences the regional climate. Rainfall is especially sensitive to ENSO phases (i.e., El Niño, La Niña and Neutral) in Florida with an average excess near 40% during an El Niño year, and with deficit close to 30% during a La Niña year. Temperature is also affected by ENSO. Lower (higher) temperatures, especially before planting season, are observed during El Niño (La Niña) (Jagtap et al., 2002).

In this study, crop yields for cotton and peanuts were simulated using a suite of biophysical simulation models (DSSAT v4.0, Jones et al., 2003) and 65 years of daily weather records (1939-2003), which were classified by ENSO phase.[2] Due to the limited weather data only a few realizations of ENSO impacts can be obtained. Thus following Cabrera et al. (2006), a stochastic generator was used to expand the yield records to 990 cases by ENSO phase to obtain more robust results. Table 1 present some descriptive statistics of the of synthetically generated crops yields by ENSO phase and planting dates.[3]

[TABLE 1]

To simulate the necessary farm income series, synthetic prices series were generated according to Letson et al. (2005). In doing so, several steps were performed. First, monthly average prices received by Florida farmers for peanut and cotton were obtained from the USDA National Agricultural Statistical Service. The price series, which included data from January 1996 to January 2005, were deflated to January 2005 dollars using the U.S. Consumer Price Index. In addition, this data was 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. The sampled values were combined and back transformed to reconstruct crop price residuals. The Kolgomorov-Smirnov tests confirmed that the correlation structure of the 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 dates of the two crops were re-introduced: 2 September - 6 November for peanut and 22 September - 28 December for cotton. The price distributions obtained with this method do not represent historical values, but rather distributions consistent with historical variability.

Contemporary local (variable and fixed) costs of production and labor requirements were deterministically incorporated in the model. The data for the two crops were provided by the North Florida Research and Education Center in Quincy, Florida. The annual variable costs for peanut and cotton are, respectively, $1,088/ha and $1,122/ha. The fixed costs are $344/ha for peanut and $177/ha for cotton.

Lastly, to provide more realistic farm scenarios and to reduce the number of decisions in our model, the most common insurance products used by farmers in the Jackson County were used in the analysis. Specifically, the studied crop insurance products for peanut and cotton were: CAT or Catastrophic coverage; and, 65, 70 and 75%APH or Actual Production History (a.k.a., MPCI Multi-Peril Crop Insurance). Additionally, 65, 70, 75, 80, 85%CRC or Crop Revenue Coverage were included for cotton. All relevant information about the implemented crop insurance products is summarized in Table 2. In this study we diverge from Cabrera et al. (2006) in which the premiums received by the insurer included both the government subsidies as well as the farmer's payment. Premiums were computed using the *Premium Calculator* at the USDA Risk Management Agency Website (http://www3.rma.usda.gov/apps/premcalc/).[4]

[TABLE 2]

5. Methodology

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

5.1 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 income, 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 incomes 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:

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

where

$$U(W_f) = \frac{W_f^{1-R_r}}{1-R_r} \,, \qquad \text{for } R_r = 0, 0.5, 1, 2, 3, 4 \qquad (2)$$

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

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);

$\boldsymbol{j}$ = crop (1 = peanut, 2 = cotton);

$\boldsymbol{m}$ = planting date in Table 1 (1 to 9 for peanut, and 10 to 13 for cotton);

$\boldsymbol{n}$ = 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);

$\boldsymbol{R_r}$ = constant risk aversion coefficient;

Π = income;

$\boldsymbol{W_0}$ = initial wealth;

$\boldsymbol{W_f}$ = final wealth;

$\boldsymbol{Y}$ = crop yield;

$\boldsymbol{IY}$ = indemnity yield for insurance purposes (i.e., the compensation a farmer receives to cover losses below insured yield levels);

$\boldsymbol{P}$ = crop price;

$\boldsymbol{PB}$ = price base for insurance purposes;

$\boldsymbol{C}$ = production cost;

$\boldsymbol{Pr}$ = insurance premium; and,

$\boldsymbol{X}$ = 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.

5.2 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. As in the farmer’s case, the model assumed the farmer requires selecting at least some type of insurance contract for each cultivated crop, cotton and peanut, having 50% 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:

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

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).[5] 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. In doing so, the objective to minimize loss returns (*L*) is constrained under a CVaR (Equation 7), so as the insurer can control the risk (α) associated to a combination of insurance contracts to reach a loss inside a defined range (*v*).[6]

Both optimization models (i.e., farmer' and insurer's models) 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.

6. Results and Discussion

6.1 Farmer's Best Performing Crop Insurance Combinations

Table 3 presents the farmer's best performing crop insurance combinations under different risk aversion levels. These crop insurance combinations were selected based on the estimated farm incomes for a single 990-year planning horizon. As expected, the yearly average predicted income decreased with increased risk aversion levels. In addition, a comparison of farm income between the ENSO phases and 'all years' shows that the latter displays statistically lower average incomes than the ENSO phases. However, no statistically significant differences were found between El Niño and La Niña years.[7] Lower incomes for 'all years' are expected since this group did not include climate forecasts information in its farm decisions framework. The income difference between any ENSO phase and 'all years' could be considered as the added value of using climatic information.

[TABLE 3]

The empirical results show that, independently of the ENSO phase, higher incomes were simulated for low or no insurance coverage for cotton combined with high coverage for peanut. The highest income was 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 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 $CI_{(95\%)}$=[11,741-14,154]).

As indicated above, differences were also found depending on the farmer's risk aversion level. For low risk adverse 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 neutral

(R_r = 0) and normal (R_r = 1) risk aversion levels, the best crop insurance combination are no coverage or CAT coverage for cotton and 65 to 75% APH for peanut.

For higher risk aversion levels (R_r = 2, 3 and 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 as one of the 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. For peanut, however, lower coverage levels were selected such as no insurance and 65%APH for El Niño years; no insurance, 65 to 75%APH for Neutral years, and 70%APH for La Niña years. Crop insurance coverage is just one of the ways that farmer 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 not necessarily by buying more crop insurance. The trade off is increased financial risk versus reduced production risk. The risk adverse farmer would find for the case of peanut that the cost of insurance premium is more risky than the additional protection provided by the insurance.

6.2 Insurer's Best Performing Crop Insurance Combinations

The optimization analysis for the insurer shows average gains ranging from \$23 to \$258 ha/year. Minimum gain occurred for a contract CAT for cotton and 70%APH for peanut for La Niña and El Niño years, whereas this was 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 2 summarizes the average gains by insurance contracts and ENSO phase. The lines cross over in several points indicating different climate impacts by insurance contract.

[FIGURE 2]

Table 4 shows the crop insurance contracts with maximum gains that 90, 95, or 99% of the time (risk level) have more gain than a value (risk value). The contract 85%CRC-65%APH was the best for El Niño years, however if the insurer wants to have higher than $4,000 of gain (or $100/ha) 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) would be 75% APH-CAT. There was no contract available that 99% of the time had a gain greater than $4,000.

[TABLE 4]

6.3 Synergies and Conflicts between Farmer and Insurer

Figure 3 combines the farmer net income and the insurer gains, both expressed as percentages of their maximums, by ENSO phase and crop insurance contract. Following the model presented in Section 3, synergies between insurer and farmer can be found in areas where percentages of insurer gain and farmer net income 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 out some synergic crop insurance alternatives. Specifically, the synergic crop insurances are: 75%APH-75%APH and 75%CRC-CAT for all ENSO phases; 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.

[FIGURE 3]

The greater conflict of interest between insurer and farmer occurred at the extremes of the graphs in Figure 3. The contract 85%CRC-CAT was the lowest net income 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 highest net incomes for the farmer with the lowest gains for the insurer.

6.4 Insurer Loss Ratios by Optimal Crop Insurance Contracts

Lastly, we discuss the insurer loss ratios obtained under optimal crop insurance contracts presented earlier. Generally speaking, a loss ratio corresponds to what an insurer spends to pay the claims of its customers, expressed as a percentage of its premium. The loss ratio is a fair measure of the value of an insurance product from a consumer perspective. 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. 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 4 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 highest ratios occurred for CAT-75%APH for El Niño, 65%CRC-70%APH for Neutral, and CAT-70%APH during La Niña.

[FIGURE 4]

The results presented above are far from the 1.075 long-run loss ratio targeted by the Federal Crop Insurance Corporation (FCIC) in 2005.[8] 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 5 shows that most of the contracts had a number of realizations that reached such a 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 5]

Climate variability had a great impact on the farmer income and insurer gain, impacting also the overall loss ratio and the probability to reach the 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 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.

7. Concluding remarks

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 farmer's income 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 income and insurer gains according to crop insurance contracts.

While 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 the 1.075 long-run ratio targeted by policy makers; suggesting that for the region and crops considered significant room exists for decreasing subsidies and/or decreasing farmers' premium, while still attaining economically feasible loss ratio targets.

In sum, the results of this study agree with the spirit of Changnon, Fosse and Lecomte (1999) who suggest that usable and timely 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 maximize their incomes. 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 income could be an area for future refinement of the model implemented here.

Footnotes

[1] Our framework may not be a good approximation for some particular federal farm programs in which crop insurance products have been developed without taking into account the insurer losses. However, long-term sustainability of crop insurance programs will require maintaining those losses to a manageable level. Thus, optimizing insurers losses would help in reaching this goal.

[2] The climate information was collected from the weather station at Chipley, Florida. Additionally, the JMA (1991) definition of ENSO events was used to sort the climate data.

[3] It is important to indicate that our simulated yields are consistent with previous research in Florida (e.g., Hansen, Hodges and Jones, 1998; Mavromatis, Jagtap and Jones, 2002; among others).

[4] Ongoing farm policy discussions may affect commodity prices and crop insurance contracts. For example, cotton export subsidies could be reduced or eliminated, due to international trade negotiations (USTR, 2006). If so, domestic cotton prices may decline and become more volatile, which in turn may trigger more expensive insurance contracts. Thus, the optimum selection of insurance contract may be affected not only by the new insurance premiums, which are also likely to be redefined in the new 2007 Farm Bill, but also by commodity prices and risk preferences. Nevertheless, the framework implemented in this paper holds valid in analyzing synergies and conflicts between farmers and insurers in future venues.

[5] Different risk levels are included in this analysis to control for climate uncertainty and for uncertainty about the honesty of the insured (Moral Hazard).

[6] A detailed mathematical derivation of the CVaR model in agriculture can be found in Liu et al. (2006).

[7] Independent *t*-tests (α=0.05) were used to compare the average farm income.

[8] The local insurer's loss ratios reported in this paper consider only two crops in one county and are not intended for evaluating the whole U.S. insurance market. To do so, further analysis including a broader spatial a dimension is needed.

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Table 1. Descriptive Statistics: Synthetic Yields by Crops and Planting Date

Crop	Planting date	Synthetic yields (kg/ha)							
		All Years		El Niño		Neutral		La Niña	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Peanut	16 April	3,078	1,275	2,918	1,308	3,261	1,507	3,055	916
	23 April	3,150	1,276	3,077	1,339	3,151	1,471	3,221	961
	1 May	3,217	1,272	3,150	1,232	3,202	1,474	3,298	1,076
	8 May	3,332	1,318	3,303	1,235	3,338	1,430	3,356	1,282
	15 May	3,360	1,225	3,313	1,146	3,278	1,257	3,489	1,260
	22 May	3,361	1,210	3,390	1,064	3,352	1,248	3,341	1,305
	29 May	3,373	1,266	3,402	1,224	3,371	1,201	3,346	1,368
	5 June	3,341	1,327	3,440	1,389	3,288	1,238	3,296	1,344
	12 June	2,956	1,477	3,008	1,613	2,982	1,376	2,877	1,429
Cotton	16 April	720	78	720	78	729	84	711	69
	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
Number of observations		2,970		990		990		990	

Note: Planting dates are based on stand agricultural practices in the Southeastern U.S.

Table 2. Crop insurance policies, coverage levels, premium prices, and average yields used in the farm model analysis

	Peanut	Cotton
APH coverage range (5% increments)	65 - 75%	65 - 75%
CRC coverage range (5% increments)	--	65 - 85%
Price Base 2004 ($/kg)	0.393	1.499
APH Premium Range 2004 ($/ha)	9.64 - 41.27	21.50 - 93.90
CRC Premium Range 2004 ($/ha)	--	27.18 - 288.87
Average yield (Ton/ha)	3.362	0.729

Note: APH is yield and **CRC** is income coverage.

Source: USDA Risk Management Agency

Table 3. Farmer's best crop insurance combinations according to average incomes by ENSO phase and level of risk aversion.

Level of Risk Aversion *(R_r)*	El Niño		Neutral		La Niña	
	Insurance (Cotton – Peanut)	Average Income ($ / yr)	Insurance (Cotton – Peanut)	Average Income ($ / yr)	Insurance (Cotton – Peanut)	Average Income ($ / yr)
0 Risk Neutrality	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 Normal Risk Aversion	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 Rather Averse	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 Very Averse	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 Almost Paranoid	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

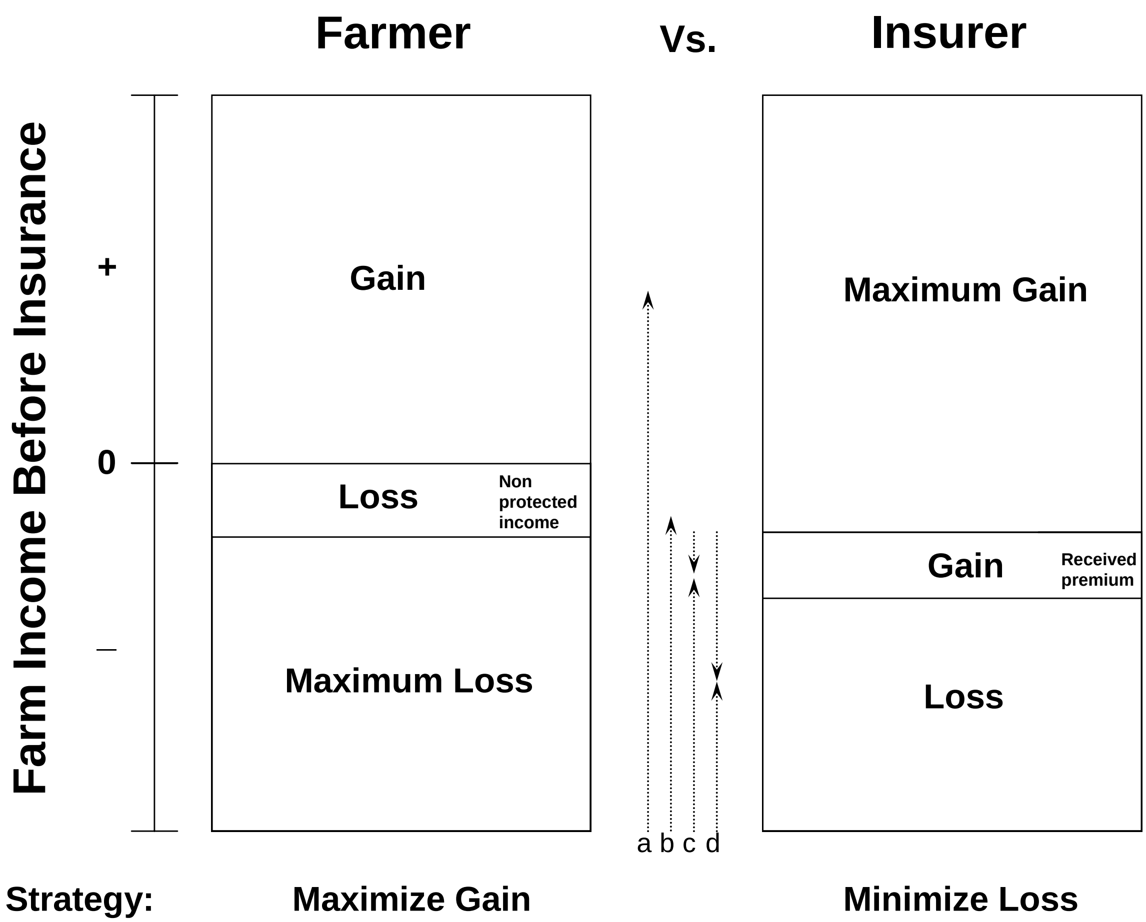
Note: Insurance is cotton-peanut insurance combination; **CRC** is crop revenue coverage; **APH** is actual production history; **CAT** is catastrophic coverage; and **NOINS** is no insurance.

Table 4. Insurer's best crop insurance contract according to risk values and risk levels

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

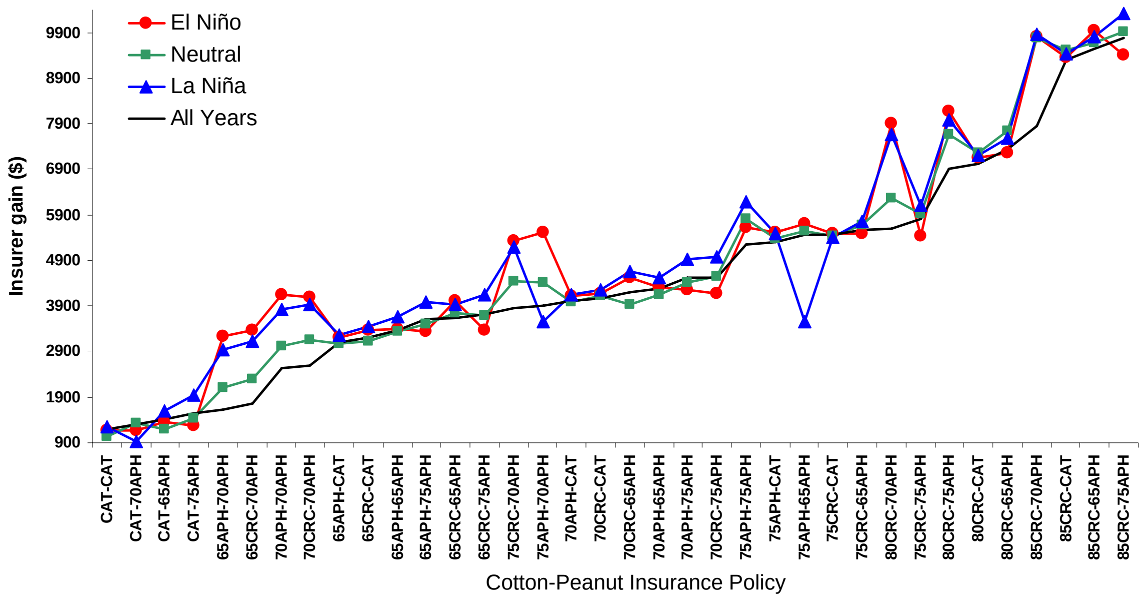
Note: **NA** means not available insurance contract for those conditions. Crop insurance contracts (%) are for cotton-peanut combinations.

Figure 1. Gains, losses, and risk strategies in determining the best crop-insurance contract: farmer and insurer synergies and conflicts



Note: upside arrows identify farm incomes and downside arrows represent indemnity payments.

Figure 2. Average gain of insurer per crop insurance contract and ENSO phase



Note: Crop insurance contracts (%) are for cotton-peanut combinations

Figure 3. Insurer gain and farmer net income expressed by percentage of their maximums by crop insurance contract and ENSO phase.

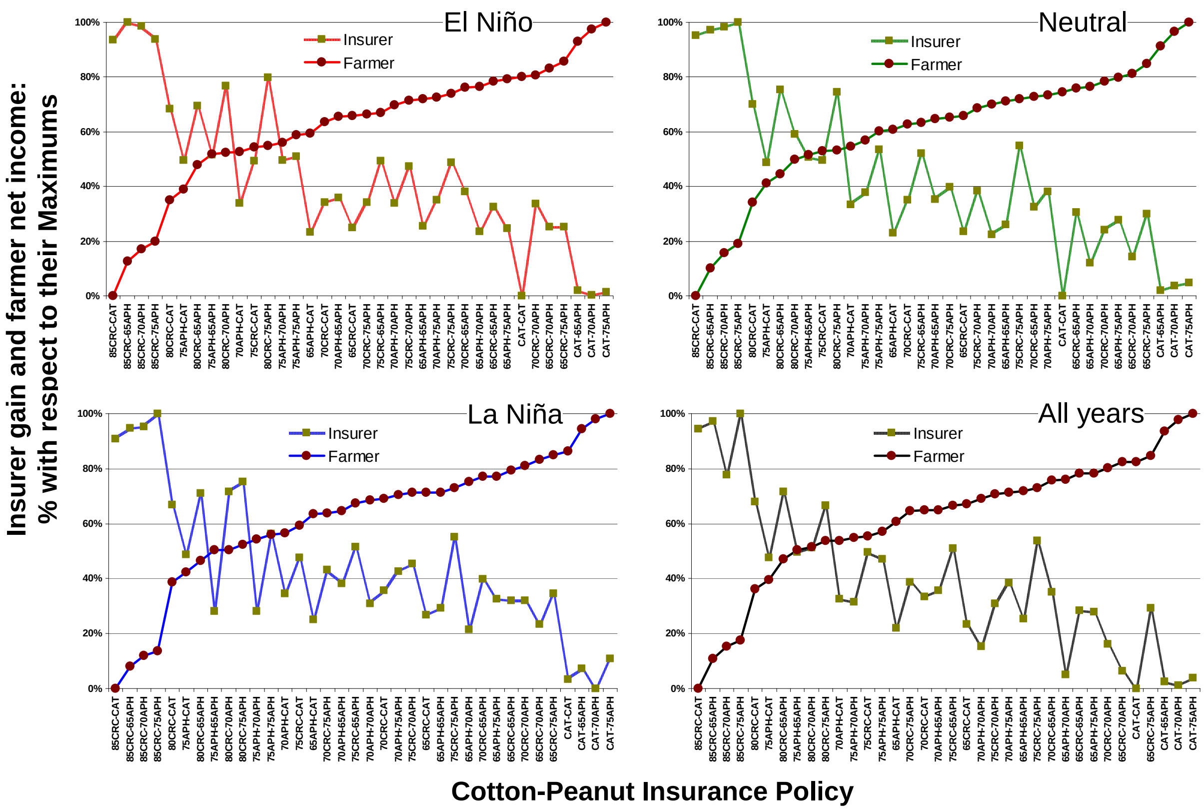


Figure 4. Average loss ratio per crop insurance contract and ENSO phase

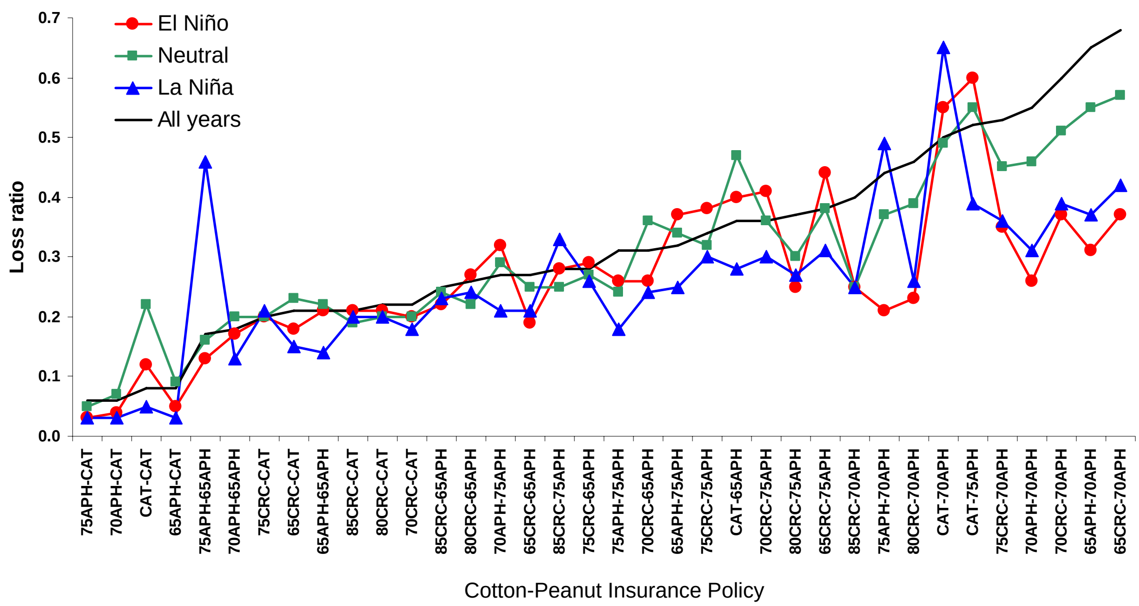


Figure 5. Frequency or number of times the loss ratio was between 1 and 1.075 per crop insurance contract and ENSO phase.