Optimizing Crop Insurance under Climate Variability

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ABSTRACT

This paper studies the selection of optimal crop insurance under climate variability and fluctuating market prices. A model was designed to minimize farmers' expected losses (including insurance costs) while using the conditional-value-at-risk measure to acquire the risk-aversion level. The application of the model was illustrated by studying a farm with two crops (cotton and peanut) in Jackson County, Florida. The climate variability was caused by ENSO phenomenon. Crop-insurance contracts with minimized losses were 75% actual production history (APH) during El Niño and neutral years and 65% APH during La Niña years for peanut and 75% APH in all ENSO phases for cotton. In addition, risk-averse farmers could select 75% APH for peanut during La Niña years as a means of attaining less expected loss.

1. Introduction

The climate and market risks have substantial impact on the performance of the crop industry. One way for farmers to reduce these risks is to purchase appropriate crop-insurance products. There are numerous crop-insurance products available in the market, and therefore it is meaningful to study the optimal crop-insurance selection strategy. In some regions, crop production is heavily dependent on climate conditions in El Niño–Southern Oscillation (ENSO; Trenberth 1997) phases characterized by sea surface temperature (SST; Niño-3.4 definition) anomalies in the eastern equatorial Pacific Ocean (Cabrera et al. 2006). The ENSO phenomenon is associated with climate variability from year to year in many parts of the world. When SST in the eastern equatorial Pacific Ocean is higher than normal, the phenomenon is referred to as El Niño; when it is lower than normal, the phenomenon is referred to as La Niña. Neutral is the term for when neither El Niño nor La Niña are present in the Pacific. In the southeastern United States, ENSO impacts are well documented (Ropelewski and Halpert 1986; Rogers 1988; Sittel 1994; Green et al. 1997). El Niño effects on climate are strongest in the southeastern United States during winter and spring, bringing more rainfall and cooler temperatures. La Niña brings warmer and drier winters (Green et al. 1997). Recent advances in climate forecasting provide opportunities to improve the management of climate-associated risks in agriculture (Hansen et al. 1998). Use of ENSO-based climate forecasts has been shown to help to reduce risks faced by

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agricultural enterprises (Hansen 2002; Jones et al. 2000). Fraisse et al. (2005) and Cabrera et al. (2006) demonstrated the ability to use ENSO-based climate forecasts combined with crop-growth models to aid the crop-insurance industry.

Crop insurance is a major component of risk management that farmers could use together with climate information to optimize their risk–return characteristics (Changnon et al. 1999). Three main types of crop insurances are the actual production history (APH) or multiperil crop insurance (MPCI), the crop revenue coverage (CRC), and the catastrophic coverage (CAT). APH assures a percentage of the farmers' historic yield. If the yield becomes lower than the insured percentage, the insurance pays an indemnity covering the difference between the insured percentage and the low yield. CRC assures income by indemnifying farmers based on historical yield and a prefixed market price, which is also called the price election. [This price is set by the Federal Crop Insurance Corporation (FCIC) before the sales closing date for the crop.] If the actual yield multiplied by the actual market price is lower than an indemnified income level, farmers are entitled to an indemnity payment. CAT can be defined as an APH policy at 50% yield coverage with 55% price-base election.

Only a few studies have explored the interactions between common crop-insurance contracts and ENSO-based forecasts (Cabrera et al. 2006, 2007; Mjelde and Hill 1999; Mjelde et al. 1996; Letson et al. 2005). Cabrera et al. (2007) and Letson et al. (2005) presented a systematic study to strategize the selection of crop-insurance products under climate variability. They analyzed risks associated with each ENSO phase, based on long series of synthetic crop yields and independent synthetic commodity prices. They identified optimal planting dates and crop-insurance products by maximizing the farmers' expected utility for different risk-aversion levels. The expected utility they considered is a power function of the initial wealth of farmers. In addition they used five plausible levels of risk aversion. It is usually difficult to evaluate the expected utility for three reasons. First, the wealth of an economic enterprise is the sum of the initial wealth and the new gain, but it is not easy to assess the initial wealth. Second, the risk measure is introduced as a power function of wealth, which makes the model a complex stochastic nonlinear optimization problem. Third, there are only five ranges for the risk-aversion level, which is a limited number of ranges.

In this study, we optimize farmers' expected loss directly. The major difference between this study and Cabrera et al. (2006) is that we use a different risk measure called the conditional value-at-risk (CVaR) (Rockafellar and Uryasev 2000, 2002) instead of the expected utility to model farmers' risk preference. CVaR is defined using the α-percentile of a random variable. For a continuous random variable ξ, its α-percentile is the value ζ such that $\Pr(\xi \le \zeta) = \alpha$, where Pr is the probability function. For instance, for a standard normal random variable ξ, its 0.5 percentile is $\zeta = 0$ and its 0.975 percentile is $\zeta = 1.96$. The α-percentile is called value-at-risk (VaR) in finance applications. By definition, for continuous distributions, conditional-value-at-risk is the average value of the random variable exceeding its α-percentile. For instance, the 97.5% CVaR of a standard normal random variable ξ is the expectation of ξ exceeding 1.96, or $E(\xi | \xi > 1.96)$, where E stands for the expectation. However, for discrete distributions, CVaR may not equal the conditional expectation; it is equal to the α-tail expectation (Rockafellar and Uryasev 2002). Figure 1 shows a simple illustration of CVaR.

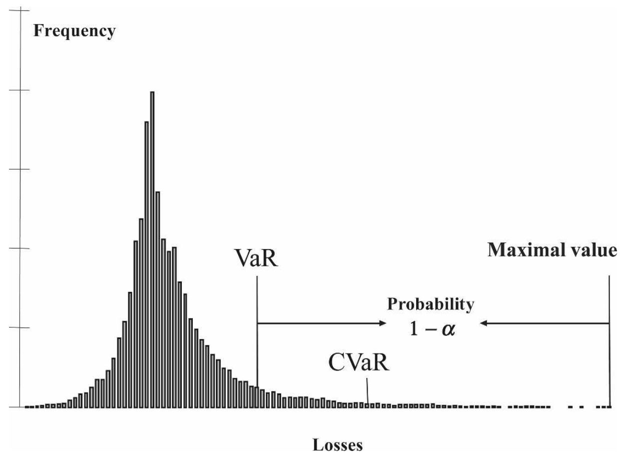

FIG. 1. Loss distribution, α-VaR and α-CVaR.

CVaR has some attractive properties over the expected utility. First, the risk-aversion level is specified in simple monetary terms with some confidence level. (It is easy for farmers to decide their own levels of personal risks.) For example, the statement "90% CVaR must be less than \$100" means the average loss of the worst 10% of outcomes must be less than \$100. Second, CVaR is a statistical characteristic depending upon the distribution of outcomes, and therefore it can model risk-aversion levels without the expected utility. Third, CVaR is very similar to VaR, which is a standard measure used in various engineering applications (Rockafellar and Uryasev 2002). Fourth, CVaR is a *coherent measure of risk* [as defined by Artzner et al. (1999)] with axiomatic-mathematical properties that are desirable for a "perfect risk measure." Fifth, Rock-

TABLE 1. Model parameters.

Variable	Unit	Description
C_k	$ ha^{-1}	Production cost of crop k per hectare
$R_{i,k}$	$ ha^{-1}	Premium of the insurance policy i for crop k per hectare
P_k^s	$ kg^{-1}	Market price of crop k per kilogram for scenario s
P_k^*	$ kg^{-1}	Price election of crop k, i.e., the expected market price per kilogram; this price is set by FCIC before the sales closing date for the crop
$y_{d_k}^s$	kg ha^{-1}	Yield of crop k per hectare for planting date d_k in scenario s
$y_{i,k}^*$	kg ha^{-1}	Insured yield of crop k per hectare by policy i

afellar and Uryasev (2000) showed that CVaR of a discrete random variable is a convex piecewise linear function that can be optimized with linear programming. Sixth, CVaR is more conservative than VaR because of the facts that CvaR ≥ VaR and that it measures outcomes in the tail (beyond VaR). CVaR is an exceptional risk measure, and it is gaining popularity in various applications, especially in finance (Rockafellar and Uryasev 2002).

The main goal of this study is to present a new decision-making method by designing a model to help farmers to buy crop-insurance products according to realistic risk-aversion levels included in the CVaR function. In addition to the optimal crop-insurance selection, the model would help farmers to allocate land to different planting dates for the included crops. We test the model by applying it to a cotton/peanut farm in Jackson County, Florida.

2. The model

Let us assume that a farmer can plant multiple types of crops on different planting dates and that he or she can allocate arbitrary land area and choose a different insurance policy for each crop. His or her task is to buy the appropriate crop-insurance policies, to decide on the best planting dates, and to allocate the appropriate area to each crop. In reality, the ENSO phase of the coming year is known to farmers before they make their decisions, and therefore they can use the climate information to optimize the expected revenue sustaining their risk-aversion level (i.e., the worst-case loss).

Analyses were performed for all three ENSO phases separately occurring during a period of 65 yr (1939–2003). The objective is to minimize the expected loss subject to a risk-aversion constraint represented using CVaR. The number of scenarios is equal to the number of possible yields and market prices (historical data). The decision variables are the amount of land allocated to every planting date and the crop-insurance products selected.

a. Notations

It is assumed that the farm grows K types of crops and allocates area q_k, $k = 1, 2, \ldots, K$, for each crop. The possible planting dates for a crop k are indexed by d_k. Scenarios indexed by $s = 1, 2, \ldots, N$ are historical records for each ENSO phase. Crop-insurance contracts are indexed by $i = 1, 2, \ldots, I$. Parameters used for each outcome are listed in Table 1.

The decision variables are X_{d_k}, which is the number of hectares of land for crop k with planting date d_k, and $\lambda_{i,k}$, which is the selection of insurance policy for crop k (binary), where $\lambda_{i,k}$ is 1 if the farmer selects policy i for crop k and otherwise is 0. The following equalities are valid:

$$\sum_i \lambda_{i,k} = 1, \quad \text{for} \quad k = 1, 2, \ldots, K,$$

because the farmer buys only one insurance policy for each crop $k = 1, 2, \ldots, K$.

b. ENSO phases and climatic component

Daily rainfall and maximum and minimum temperatures for Jackson County from 1939 to 2003 (65 yr) collected at the Chipley weather station (30.783°N, 85.483°W) were used to run crop-yield simulations. Each of these 65 yr was classified as belonging to an ENSO year (i.e., El Niño, La Niña, or neutral), which begins in October and runs through September of the next calendar year, according to the Japan meteorological index (Meyers et al. 1999). During this period of time, 14 yr were classified as El Niño, 16 yr were classified as La Niña, and the remaining 35 yr were classified as neutral. The limited duration of the weather records provided only a few realizations of the ENSO impacts on crop yield; however, a thorough assessment of ENSO-phase-strength uncertainty requires a more complete account of ENSO events. We consequently used the Cabrera et al. (2007) approach of using a stochastic yield generator based on simulated crop yields to resample the yields and to generate 990 stochastic yield records for each of the ENSO phases to account for their inherent uncertainty. The generated yield distributions are not historical values, but rather are distributions consistent with the historical variability associated with ENSO climatic conditions. Stochastic distributions of uncertain cotton and peanut yields relative to ENSO phases were introduced in the optimization model to perform stochastic optimizations.

c. Objective

The objective is to minimize the expected losses (or, equivalent, to maximize the expected revenue). The cost per crop is composed of the production cost, the insurance-premium cost, and the operations cost. The total revenue includes the revenue from selling of the actual yield and that from the insurance indemnity, if received. Here, Y^s_k is the total yield of crop k in scenario s; that is,

$$Y^s_k = \sum_{d_k} X_{d_k} y^s_{d_k}.$$

Let $Z^s_{i,k}$ be the difference between the insured yield and the true yield:

$$Z^s_{i.k} = \sum_{d_k} X_{d_k}(y^*_{i,k} - y^s_{d_k});$$

thus the indemnity yield is $(Z^s_{i,k})^+ = \max(0, Z^s_{i,k})$. The loss function is

$$f(\tilde{x}, \tilde{\xi}) = \sum_{k=1}^{K}\left\{C_k q_k - Y^s_k P^s_k + \sum_{i=1}^{I}\lambda_{i,k}[R_{i,k}q_k - (Z^s_{i,k})^+ P^*_k]\right\},$$

which means total loss is equal to production cost minus indemnity gain plus insurance-premium cost minus market gain. Substituting Y^s_k and $Z^s_{i,k}$ into the loss function gives

$$f(\tilde{x}, \tilde{\xi}) = \sum_{k=1}^{K}\left\langle C_k q_k - \left(\sum_{d_k} X_{d_k} y^s_{d_k}\right)P^s_k + \sum_{i=1}^{I}\lambda_{i,k}\left\{R_{i,k}q_k - \left[\sum_{d_k} X_{d_k}(y^*_{i,k} - y^s_{d_k})\right]^+ P^*_k\right\}\right\rangle, \tag{1}$$

where $\tilde{\mathbf{x}} = \{X_{d_k}, \lambda_{i,k}\}$ is the decision vector and $\tilde{\boldsymbol{\xi}} = \{Y^s_k, P^s_k\}$ is the random vector. We minimize the expected cost: $\min E[f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}})]$, where E denotes the expectation of a random variable.

d. Constraints

The most significant constraint for this minimization problem is the risk-aversion constraint measured using CVaR, which is the average of values exceeding α-percentile of a random variable. Because the loss function is a random variable depending on decision variables, the farmer can optimize the expected loss exceeding a certain value (α percentile) by changing the values of the decision variables.

The farmer can control the expected loss exceeding VaR and assure that it is less than a certain threshold value υ. This is modeled using CVaR as follows:

$$\mathrm{CVaR}_\alpha[f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}})] \le \upsilon, \tag{2}$$

where $f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}})$ is the loss function, and $\alpha = \Pr[f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}}) \le \mathrm{VaR}]$ is the confidence level, where Pr[] is the probability function.

There are two additional constraints associated with the decision variables. First, we assume the farm could grow q_k ha of crop k. Because every crop has d_k different planting dates, the sum of the area allocated to these planting dates X_{d_k} should equal the total area available; that is,

$$\sum_{d_k} X_{d_k} = q_k \quad \text{and} \quad X_{d_k} \ge 0, \quad \text{for} \quad k = 1, 2, \ldots, K. \tag{3}$$

Second, we assume the farmer could buy no more than one type of insurance policy for every crop. Binary variables $\lambda_{i,k}$ are used to represent this condition:

$$\sum_i \lambda_{i,k} = 1, \quad \text{for} \quad k = 1, 2, \ldots, K. \tag{4}$$

e. Complete model formulation

Putting all the conditions together, we express this optimization problem as minimize $E[f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}})]$ such that

$$f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}}) = \sum_{k=1}^{K}\left\{C_k q_k - Y^s_k P^s_k + \sum_{i=1}^{I}\lambda_{i,k}[R_{i,k}q_k - (Z^s_{i,k})^+ P^*_k]\right\},$$

$$Y^s_k = \sum_{d_k} X_{d_k} y^s_{d_k},$$

$$Z^s_{i.k} = \sum_{d_k} X_{d_k}(y^*_{i,k} - y^s_{d_k}),$$

$$\sum_{d_k} X_{d_k} = q_k \quad \text{and} \quad X_{d_k} \ge 0, \quad \text{for} \quad k = 1, 2, \ldots, K,$$

$$\sum_i \lambda_{i,k} = 1, \quad \text{for} \quad k = 1, 2, \ldots, K,$$

where $\lambda_{i,k}$ are binary numbers, and

$$\mathrm{CVaR}_\alpha[f(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\xi}})] \le \upsilon.$$

TABLE 2. Crop-insurance products, coverage levels, premium prices, and average yields used in the farm model analysis, from Cabrera et al. (2006).

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

3. Case study

We use the same dataset as in the case study of Cabrera et al. (2006). We optimize a 40-ha nonirrigated farm in Jackson County that allocates one-half of its land to cotton and one-half of its land to peanut. For cotton, there are four planting dates: 16 April, 23 April, 1 May, and 8 May. For peanut, there are nine planting dates, two dates in April, five dates in May, and two dates in June. These dates are set according to the current management practices in the southeastern United States. Crop-insurance products include the most popular contracts, listed in Table 2.

A farmer can choose either "no insurance" or one of three types of insurance products for each crop. Including the no-insurance option, there are 5 options for peanut and 10 for cotton. The total of possible selections of crop-insurance combinations for cotton and peanut is 50. The price of the insurance premium depends on the type of the policy, coverage level, location, and historical yield, which were estimated using the premium calculator from the Risk Management Agency (http://www3.rma.usda.gov/apps/premcalc/). We use 100% of the price election for APH and CRC crop-insurance products, because they are the most common choices of farmers.

Crop yields are simulated using the models available in the Decision Support System for Agrotechnology Transfer (DSSAT), version 4.0 (Jones et al. 2003). The "CROPGRO-Peanut" (Boote et al. 1998) and "CROPGRO-Cotton" (Pathak et al. 2007) models are used. These models were calibrated and tested for management practices and environmental conditions in the southeastern United States (Mavromatis et al. 2002; Pathak et al. 2007). The crop-model simulations use the representative soil type Dothan loamy sand and the current management practices in the region for varieties, fertilization, and planting dates (Cabrera et al. 2007). In the case of peanut, the most widely planted variety in the region, Georgia Green, is used for the simulations. It is a Runner-type variety with medium maturity and moderate resistance to tomato spotted-wilt virus and to cylindricladium black rot. For cotton, the popular medium–full season Delta and Pine Land variety (DP 555) is used.

We simulate yields of cotton and peanut using climate data between 1939 and 2004 (65 yr) categorized according to ENSO phases. We also use simulated market prices of the two crops for the years between 1939 and 2004 based on 10 yr (1996–2005) of historical records from the National Agricultural Statistical Service of the U.S. Department of Agriculture (http://www.nass.usda.gov) and ENSO phases (Meyers et al. 1999). Matlab 7.01 commercial software was used to perform the optimizations.

a. *Model results without CVaR constraint*

1) OPTIMAL INSURANCE CHOICES

The model results without the CVaR constraint are shown in Fig. 2. For neutral and El Niño years, buying no insurance for cotton and 75% APH for peanut is the optimal solution; the revenue is $16,250 and $17,657, respectively. For La Niña years, buying no insurance for cotton and 65% APH for peanut is the optimal solution with revenue of $16,315. The line "all years" in Fig. 2 shows the result of optimizing without distinguishing ENSO phases. Revenues for the all-years case are lower than those from using ENSO-based information; this result demonstrates the value of including the climate information. The optimal solution for the all-years case is buying no insurance for cotton and 75% APH for peanut, coinciding with neutral and El Niño years. One explanation for selecting no insurance for cotton might be that in our case cotton insurance is expensive while cotton yield is stable. Because the cotton insurance premium and yield vary spatially, it would be desirable to replicate the study for different locations.

Figure 3 shows the distribution of revenues based on the best crop-insurance selection for three ENSO phases. For example, the figure shows that the probabilities of getting $20,000 revenue are approximately 0.17, 0.06, and 0.14 during the neutral, El Niño, and La Niña years, respectively.

2) OPTIMAL PLANTING DATES

Only one optimal planting date is selected for each crop-insurance contract and ENSO phase. For peanut,

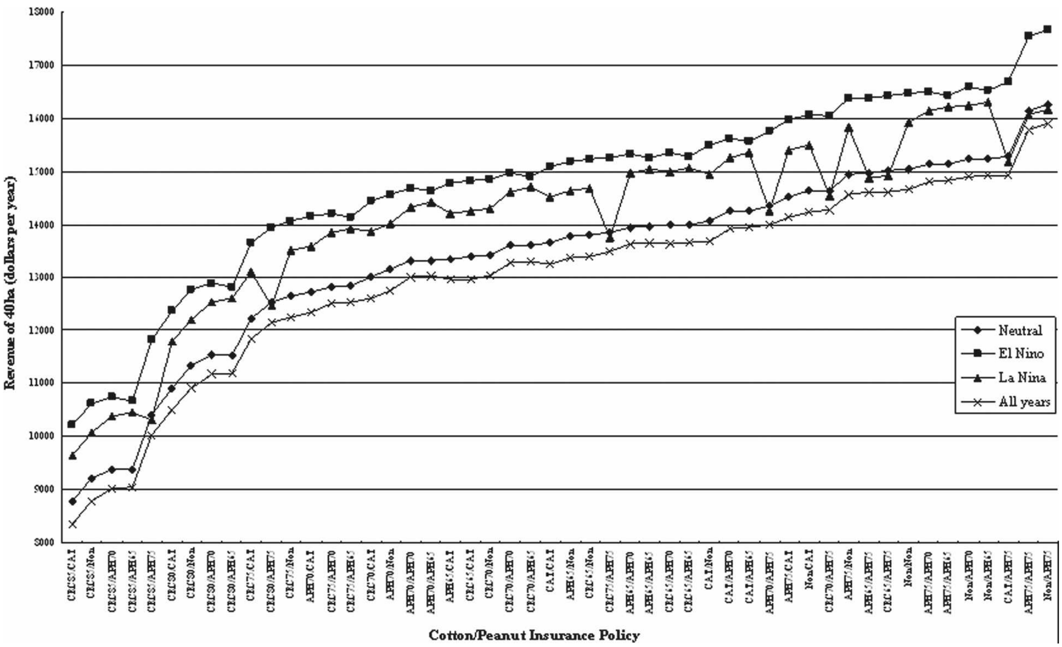

FIG. 2. Optimal revenue by crop-insurance product and ENSO phase without CVaR constraints. APH65/CRC80 means APH 65% for cotton and CRC 80% for peanut.

the best planting dates are 22 May in El Niño years and 29 May in La Niña and neutral years; for cotton, the best planting dates are 16 April in neutral years, 1 May in La Niña years, and 8 May in El Niño years.

3) RESULTS WITHOUT NO-INSURANCE OPTION

Lenders and policy makers usually push farmers to buy at least one type of crop insurance. If a farmer has to purchase at least one insurance product for both crops, the optimal insurance contract for cotton would change to 75% APH in all ENSO phases. The optimal planting dates remain the same.

b. *Results with* CVaR *constraint*

If the farmer wants to control the average of the worst 5% outcomes while maximizing the expected total profit, he or she can add the CVaR constraint with 95% limit to the optimization problem. The complete

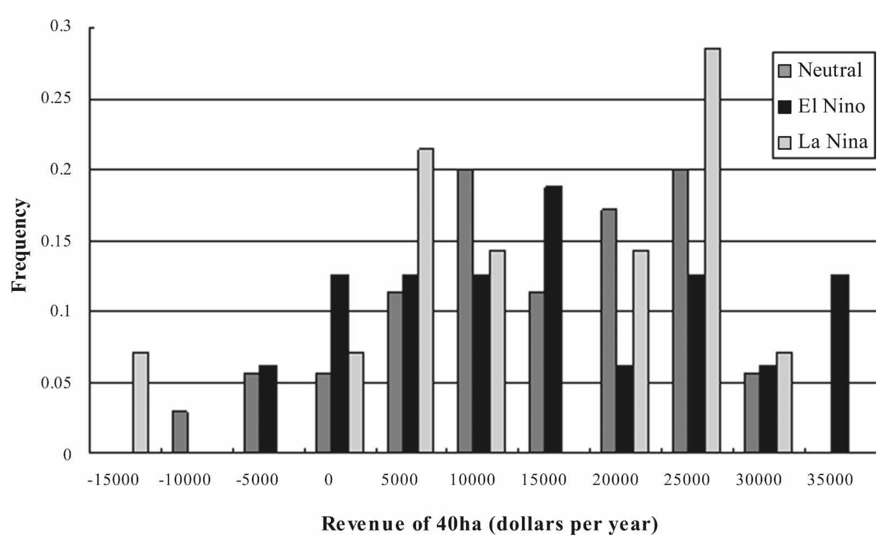

FIG. 3. Distribution of optimal income for all ENSO phases without CVaR constraint.

TABLE 3. CVaR model at 95% limit for all ENSO phases.

ENSO phase	95% CVaR limit υ	Expected revenue	Optimal insurance selection	Optimal planting date
Neutral	$6,827 and above	$16,250	Cotton: no insurance Peanut: 75% APH	Cotton: 16 Apr Peanut: 29 May
	Below $6,827	No solution	No solution	No solution
El Niño	$3,717 and above	$17,657	Cotton: no insurance Peanut: 75% APH	Cotton: 8 May Peanut: 22 May
	Below $3,717	No solution	No solution	No solution
La Niña	$10,624 and above	$16,315	Cotton: no insurance Peanut: 65% APH	Cotton: 1 May Peanut: 29 May
	Between $9,559 and $10,624	$16,235	Cotton: no insurance Peanut: 70% APH	Same
	Between $5,814 and $9,559	$16,158	Cotton: no insurance Peanut: 75% APH	Same
	Below $5,814	No solution	No solution	No solution

95% CVaR model results for all ENSO phases are shown in Table 3.

From Table 3 we can see that the expected revenue varies in accordance with the insurance-product selections. Take La Niña years as an example: if the farmer requires that the average of his or her worst 5% loss is less than $10,624, then he or she should purchase 65% APH for peanut and no insurance for cotton. If the farmer wants to reduce the average of the worst 5% loss to between $9,559 and $10,624, however, he or she should choose 70% APH for peanut and no insurance for cotton. If the farmer is extremely risk averse—that is, he or she would like to keep the average of the worst 5% loss at no more than $9,559—then 75% APH for peanut and no insurance for cotton would be the best selection. The no-insurance option for cotton in Table 3 would be replaced by 75% APH if the farmer is required to buy at least one insurance contract per crop.

We compare the distribution of the revenues by those three insurance combinations (Non/APH65, Non/APH70, and Non/APH75) during La Niña years in Fig. 4. It shows that there is 0.27 probability of having $25,000 profit but 0.07 probability of having $15,000 loss for Non/APH65 and Non/APH70. On average, the Non/APH65 and Non/APH70 selections have higher expected value and risk than does the Non/APH75 combination.

c. Sensitivity analysis

Because the input variables (yield, premium, and the base price) for peanut and cotton are dependent on the simulations, we varied their values to see how the changes would impact the output. We changed their value by 5% and 10% respectively; for instance, we might increase the premium of 70% APH for peanut by 5% and decrease the premium of 75% APH for peanut

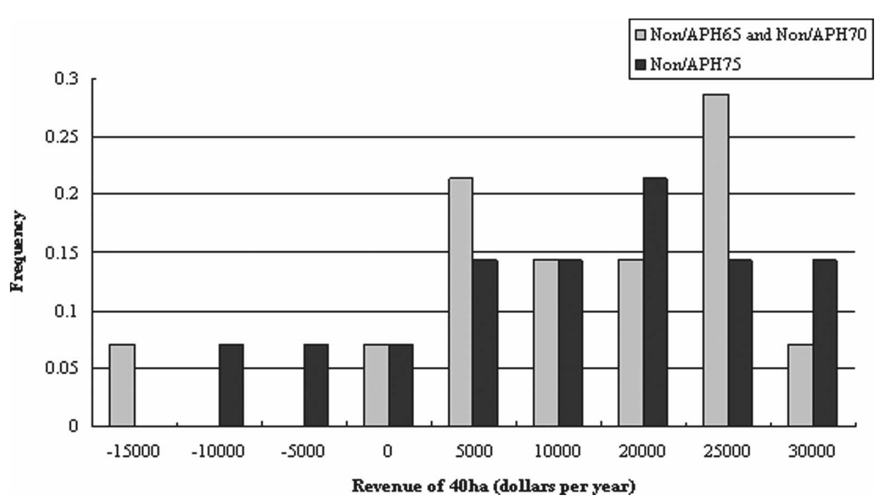

FIG. 4. The distribution of optimal revenue for La Niña years under different 95% CVaR limit values.

by 5%. We observed that the model gives the same result for both the optimal planting date and the optimal insurance selection. Hence we conclude that our model is robust.

4. Conclusions

This research studied the impact of the accuracy of the ENSO-phase forecasts and uncertain prices on crop-insurance decisions. A stochastic model was created to select optimal crop-insurance products for a certain year based on the ENSO-phase forecast. Taking advantage of the ENSO-based climate forecasts, the model can identify optimal crop-insurance products available in the crop-insurance industry.

A case study in northern Florida with a cotton/peanut farm was conducted. Results showed that the insurance choices vary under different ENSO phases and risk-aversion levels. For a risk-neutral farmer, buying no insurance for cotton and 75% APH for peanut is the optimal solution for neutral and El Niño years and buying no insurance for cotton and 65% APH for peanut is the optimal solution for a La Niña year. The insurance strategy for peanut in La Niña years changed to 70% APH for a risk-averse farmer and to 75% APH for a highly risk averse farmer. These conclusions are based on the assumption that a farmer can buy either no insurance or only one insurance product for each crop. If a farmer is required to have at least one type of crop insurance for each crop, the best selection for cotton would be 75% APH. Because the yield and the premium cost vary spatially, it is desirable to replicate the study in different places to study how the insurance selections would change across space.

Results of this study are consistent with findings of Cabrera et al. (2006). They found that the optimal policy is no insurance for cotton and 75% APH for peanut for all ENSO phases in a risk-neutral case. Also, they found that it is optimal to have 70% APH for peanut during El Niño and neutral years but 65% APH during La Niña years. However, they found CAT to be the next best option for cotton if a farmer is required to have at least one insurance contract.

Further applications of the model can be improved to include more crops, other soil types, different regions, and other insurance selections in the analyses. Moreover, the model output depends upon the quality of scenarios and estimated parameters. Market participants may have access to very different information about the same parameters. For instance, insurance companies, when compared with farmers, typically have better statistics and approaches for generating scenarios of yields and prices. Insurance companies have a history of claims for a population of farmers. Therefore, the modeling framework presented in the paper may provide better results for various users, such as insurance companies.

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REFERENCES

Artzner, P., F. Delbaen, J. M. Eber, and D. Heath, 1999: Coherent measures of risk. *Math. Financ.,* **9,** 203–228.

Boote, K. J., J. W. Jones, and G. Hoogenboom, 1998: Simulation of crop growth: CROPGRO Model. *Agricultural Systems Modeling and Simulation,* R. M. Peart and R. B. Curry, Eds., Marcel Dekker, 113–133.

Cabrera, V. E., C. Fraisse, D. Letson, G. Podesta, and J. Novak, 2006: Impact of climate information in reducing farm risk by selecting crop insurance programs. *Trans. ASABE,* **49,** 1223–1233.

——, D. Letson, and G. Podesta, 2007: The value of the climate information when farm programs matter. *Agric. Syst.,* **93,** 25–42.

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

Fraisse, C. W., J. L. Novak, A. G. Garcia, J. W. Jones, C. Brown, and G. Hoogenboom, 2005: Using crop models and climate forecasts to aid in peanut crop insurance decisions. *Extension, Circular IFAS-EDIS AE285*. University of Florida, Gainesville, 9 pp.

Green, P. M., D. M. Legler, C. J. Miranda, and J. J. O'Brien, 1997: The North American climate patterns associated with El Niño–Southern Oscillation. Center for Ocean–Atmospheric Prediction Studies Rep. 97-1, The Florida State University, Tallahassee, FL, 8 pp.

Hansen, J. W., 2002: Realizing the potential benefits of climate prediction to agriculture: Issues, approaches, challenges. *Agric. Syst.,* **74,** 309–330.

——, A. W. Hodges, and J. W. Jones, 1998: ENSO influences on agriculture in the southeastern United States. *J. Climate,* **11,** 404–411.

Jones, J. W., J. W. Hansen, F. S. Royce, and C. D. Messina, 2000: Potential benefits of climate forecast to agriculture. *Agric. Ecosyst. Environ.,* **82,** 169–184.

——, and Coauthors, 2003: The DSSAT cropping system model. *Eur. J. Agron.,* **18,** 235–265.

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

Mavromatis, T., S. S. Jagtap, and J. W. Jones, 2002: El Niño-Southern Oscillation effects on peanut yield and N leaching. *Climate Res.,* **22,** 129–140.

Meyers, S. D., J. J. O'Brien, and E. Thelin, 1999: Reconstruction of monthly SST in the tropical Pacific Ocean during 1868–1993 using adaptive climate basis functions. *Mon. Wea. Rev.,* **127,** 1599–1612.

Mjelde, J. W., and H. S. J. Hill, 1999: The effect of the use of improved climate forecasts on variable costs, input usage, and production. *Agric. Syst.,* **60,** 213–225.

——, T. N. Thompson, and C. J. Nixon, 1996: Government institutional effects on the value of seasonal climate forecasts. *Amer. J. Agric. Econ.,* **78,** 175–188.

Pathak, T. B., C. W. Fraisse, J. W. Jones, C. D. Messina, and G. Hoogenboom, 2007: Use of global sensitivity analysis for cotton model development. *Trans. ASAE,* **50,** 2295–2302.

Rockafellar, R. T., and S. Uryasev, 2000: Optimization of conditional value-at-risk. *J. Risk,* **2,** 21–41.

——, and ——, 2002: Conditional value-at-risk for general loss distributions. *J. Bank. Financ.,* **26,** 1443–1471.

Rogers, J. C., 1988: Precipitation over the Caribbean and tropical Americas associated with the Southern Oscillation. *J. Climate,* **1,** 172–182.

Ropelewski, C. F., and M. S. Halpert, 1986: North American precipitation patterns with the El Niño Southern Oscillation (ENSO). *Mon. Wea. Rev.,* **114,** 2352–2362.

Sittel, M., 1994: Differences in the means of ENSO extremes for maximum temperature and precipitation in the United States. COAPS Rep. 94-2, The Florida State University, Tallahassee, FL, 50 pp.

Trenberth, K., 1997: The definition of El Niño. *Bull. Amer. Meteor. Soc.,* **78,** 2771–2777.