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: for peanut, 75% actual production history (APH) during El Niño and Neutral years, and 65% APH during La Niña years; and for cotton, 75% APH in all El Niño Southern Oscillation phases. Additionally, risk averse farmers could select 75% APH for peanut during La Niña years as a means of attaining less expected losses.

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, so 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) phases characterized by sea surface temperature (SST, Nino 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 as El Niño; when it is lower than normal, the phenomenon is referred as La Niña. Neutral is the term for when neither El Niño nor La Niña are present in the Pacific. In the Southeast U.S.A., 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 USA 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 reduce risks faced by 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 Multi-Peril 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 pre-fixed market price, which is also called the price election. (This price is set by Federal Crop Insurance Corporation 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 5 plausible levels of risk aversion according to Hardaker et al. (1997). It is usually difficult to evaluate the expected utility for three reasons. Firstly, 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. Secondly, the risk measure is introduced as a power function of wealth, which makes the model a complex stochastic non-linear optimization problem. Lastly, there are only 5 ranges for the risk aversion level, which is rather limited.

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

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 (CVaR) 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 $E(\xi \mid \xi > 1.96)$, where E stands for the expectation. However, for discrete distributions, CVaR may not equal the conditional expectation; it equals the α-tail expectation (Rockafellar and Uryasev 2002). Figure 1 shows a simple illustration of 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's 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% outcomes must be less than \$100. Second, CVaR is a statistical characteristic depending upon the distribution of outcomes, so it can model risk aversion levels without the expected utility. Third, CVaR is very similar to Value-at-Risk (VaR), which is a standard measure used in various engineering applications (Rockafellar and Uryasev 2002). Fourth, CVaR is a *coherent measure of risk* (defined by Artzner, et. al. 1999) with axiomatic-mathematical properties desirable for a "perfect risk measure". Fifth, Rockafellar and Uryasev (2000) showed that CVaR of a discrete random variable is a convex piece-wise linear function that can be optimized with linear programming. Sixth, CVaR is more conservative than VaR due to the fact that CVaR$\geq$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 methodology by designing a model to help farmers 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 to a cotton-peanut farm in Jackson County, Florida.

2. The Model

Assume a farmer can plant multiple types of crops on different planting dates, and that he or she can allocate arbitrary land area and choose different insurance policy for each crop. His or her task is to buy the appropriate crop insurance policies, decide on the best planting dates and 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, so 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 the three ENSO phases separately occurring during a period of 65 years (1939 to 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

Assume 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,…, I . Parameters used for each outcome are listed in Table 1.

The decision variables are:

X_{d_k} = number of hectares of land for crop k with planting date d_k ;

$\lambda_{i,k}$ = selection of insurance policy for crop k (binary), where $\lambda_{i,k}$ =1 if the farmer selects policy i for crop k , otherwise $\lambda_{i,k}$ =0.

The following equalities are valid, $\sum_i \lambda_{i,k} = 1$, k =1, 2,…, K because the farmer buys only one insurance policy for each crop k =1, 2,…, K .

b. ENSO phases and climatic component

Daily rainfall and maximum and minimum temperatures for Jackson County from 1939 to 2003 (65 years) collected at the Chipley weather station (30.783° N, 85.483° W) were used to run crop yield simulations. Each of these 65 years was classified as belonging to an ENSO year (ie. El Niño, La Nina or Neutral), which began in October and runs through September of the next calendar year according to the Japan Meteorological Index (JMA, 1991). During this period of time, 14 years were classified as El Niño, 16 years as La Niña and the remaining 35 years 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. Consequently, we used the Cabrera et al. (2007) approach of using a stochastic yield generator based on simulated crop yields to re-sample the yields and generate 990 stochastic yield records for each of the ENSO phases in order to account for their inherent uncertainty. The generated yield distributions are not historical values, but 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 equivalently, 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.

Y_k^s is the total yield of crop k in scenario s, i.e., $Y_k^s = \sum_{d_k} X_{d_k} y_{d_k}^s$. Let $Z_{i,k}^s$ be the difference between the insured yield and the true yield, $Z_{i.k}^s = \sum_{d_k} X_{d_k} (y_{i,k}^* - y_{d_k}^s)$, thus the indemnity yield is $(Z_{i,k}^s)^+ = \max(0, Z_{i,k}^s)$.

The loss function equals $f(\tilde{x}, \tilde{\xi}) = \sum_{k=1}^{K} \{C_k q_k - Y_k^s P_k^s + \sum_{i=1}^{I} \lambda_{i,k} [R_{i,k} q_k - (Z_{i,k}^s)^+ P_k^*]\}$ which means

Total Loss = Production Cost - Indemnity Gain + Insurance Premium Cost - Market Gain

Substituting Y_k^s and $Z_{i,k}^s$ to the loss function gives:

$$f(\tilde{x}, \tilde{\xi}) = \sum_{k=1}^{K} \{C_k q_k - (\sum_{d_k} X_{d_k} y_{d_k}^s) P_k^s + \sum_{i=1}^{I} \lambda_{i,k} [R_{i,k} q_k - (\sum_{d_k} X_{d_k} (y_{i,k}^* - y_{d_k}^s))^+ P_k^*]\} \qquad (1)$$

Where $\tilde{x} = \{X_{d_k}, \lambda_{i,k}\}$ is the decision vector and $\tilde{\xi} = \{Y_k^s, P_k^s\}$ is the random vector.

We minimize the expected cost: $\min E(f(\tilde{x}, \tilde{\xi}))$, 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. Since 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 v. This is modeled using CVaR as follows:

$$CVaR_{\alpha}[f(\tilde{x},\tilde{\xi})] \le v \tag{2}$$

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

There are two additional constraints associated with the decision variables. Firstly, we assume the farm could grow q_k ha of crop k. Since 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, i.e.:

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

Secondly, 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:

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

e. Complete model formulation

Putting all the conditions together, we express this optimization problem as:

$$\text{Min } E(f(\tilde{x},\tilde{\xi}))$$

$$\text{S.t. } f(\tilde{x},\tilde{\xi}) = \sum_{k=1}^{K}\{C_k q_k - Y_k^s P_k^s + \sum_{i=1}^{I}\lambda_{i,k}[R_{i,k}q_k - (Z_{i,k}^s)^+ P_k^*]\}$$

$$Y_k^s = \sum_{d_k} X_{d_k} y_{d_k}^s$$

$$Z_{i.k}^s = \sum_{d_k} X_{d_k}(y_{i,k}^* - y_{d_k}^s)$$

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

$$\sum_i \lambda_{i,k} = 1, \text{ for } k = 1,2...K, \text{ where } \lambda_{i,k} \text{ are binary numbers}$$

$$CVaR_\alpha[f(\tilde{x},\tilde{\xi})] \leq v$$

3. Case Study

We use the same dataset as in the case study of Cabrera et al. (2006). We optimize a 40 ha non-irrigated farm in Jackson County, Florida that allocates half of its land to cotton and half 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 U.S. 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 possible selections of crop insurance combinations for cotton and peanut are 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 as they are the most common choices of farmers.

Crops yields are simulated using the models available in the Decision Support System for Agrotechnology Transfer (DSSAT) v4.0 (Jones et al., 2003). CROPGRO-Peanut (Boote et al., 1998) and the CROPGRO-Cotton (Messina et al., 2005) are used. These models were calibrated and tested for management practices and environmental conditions in the southeastern U.S. (Mavromatis et al., 2002; Messina et al., 2005). 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 (TSWV) and to cylindricladium black rot (CBR). For cotton, the popular medium to full season Delta & Pine Land ® variety (DP 555) is used.

We simulate yields of cotton and peanuts using climate data between 1939 and 2004 (65 years) 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 years (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 (JMA, 1991). Matlab 7.01 was used to perform the optimizations.

a. Model results without CVaR constraint

1) OPTIMAL INSURANCE CHOICES

The model results without CVaR constraint are shown in Figure 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 Figure 2 shows the result of optimizing without distinguishing ENSO phases. Revenues for “all years” are lower than those from using ENSO-based information: this demonstrates the value of including the climate information. The optimal solution for “all years” 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. Since 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, the best planting dates are 22 May in El Niño year and 29 May in La Niña and Neutral years; for cotton, the best planting dates are 16 April in Neutral year, 1 May in La Niña year and 8 May in El Niño year.

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 CVaR constraint with 95% limit to the optimization problem. The complete 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, he or she should purchase 65%APH for peanut and no insurance for cotton. But if the farmer wants to reduce the average of the worst 5% loss to between $9,559 and $10,624, he or she should choose 70%APH for peanut and no insurance for cotton. Finally, if the farmer is extremely risk aversion, i.e. he or she would like to keep the average of the worst 5% loss no more than $9,559. In this case 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 Figure 4. It shows that there is 0.27 probability of having $25,000 profit but a 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 the Non/APH75 combination.

c. Sensitivity Analysis

Since the input variables (yield, premium and the base price) for peanut and cotton are dependent on the simulations, we vary their values to see how the changes will impact the output. We change their value by 5% and 10% respectively, for instance, we may increase the premium of APH70% for peanut by 5% and decrease the premium of APH75% for peanut by 5%. We observe 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. Conclusion

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 north 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 farmer can either buy no insurance or only one insurance product for each crop. If farmer is required to have at least one type of crop insurance for each crop, the best selection for cotton would be 75% APH. Since 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 the El Niño and neutral years whereas 65% APH during La Niña years. However, they found CAT to be the next best option for cotton if 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 quite different information about the same parameters. For instance, insurance companies, compared to farmers, typically have better statistics and approaches for generating scenarios of yields and prices. Insurance companies have 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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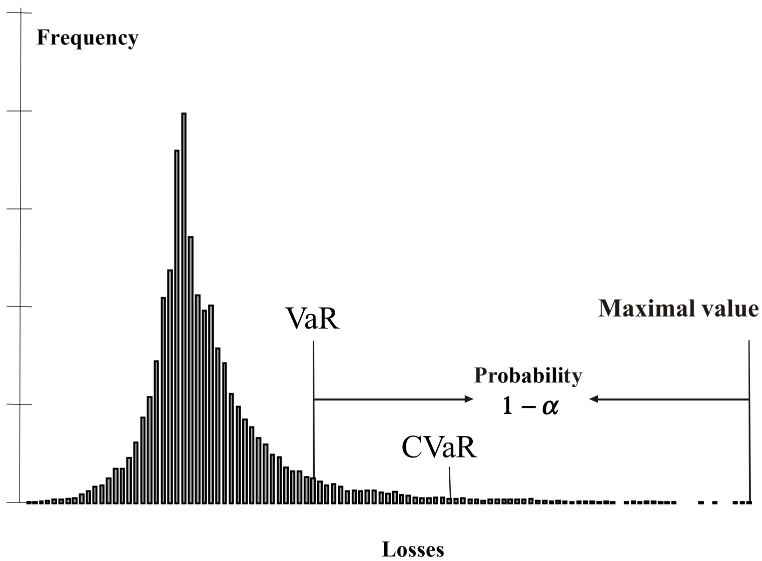
Figures and Tables

Figure 1: Loss distribution, α-VaR and α-CVaR.

Figure 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.

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

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



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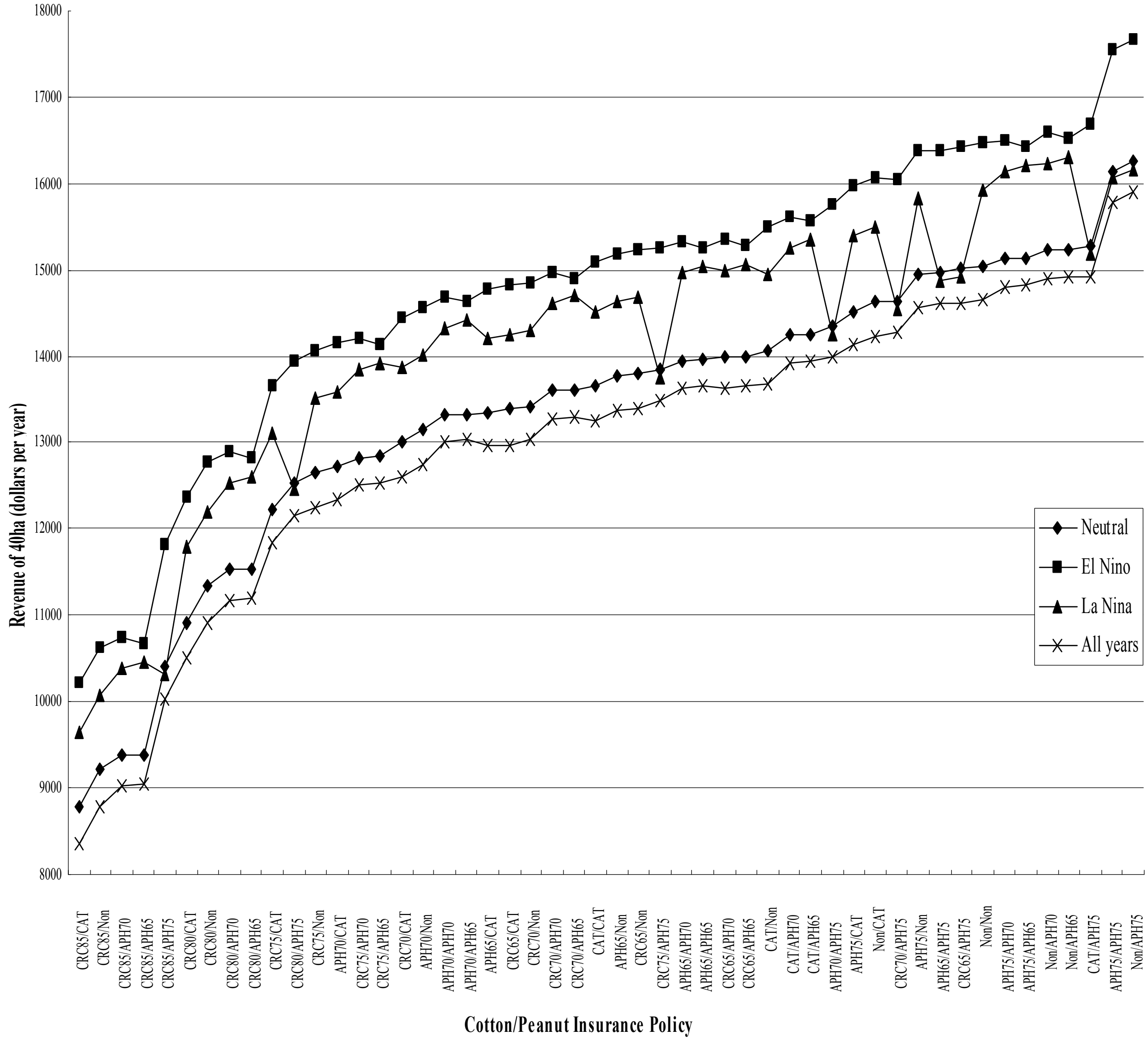

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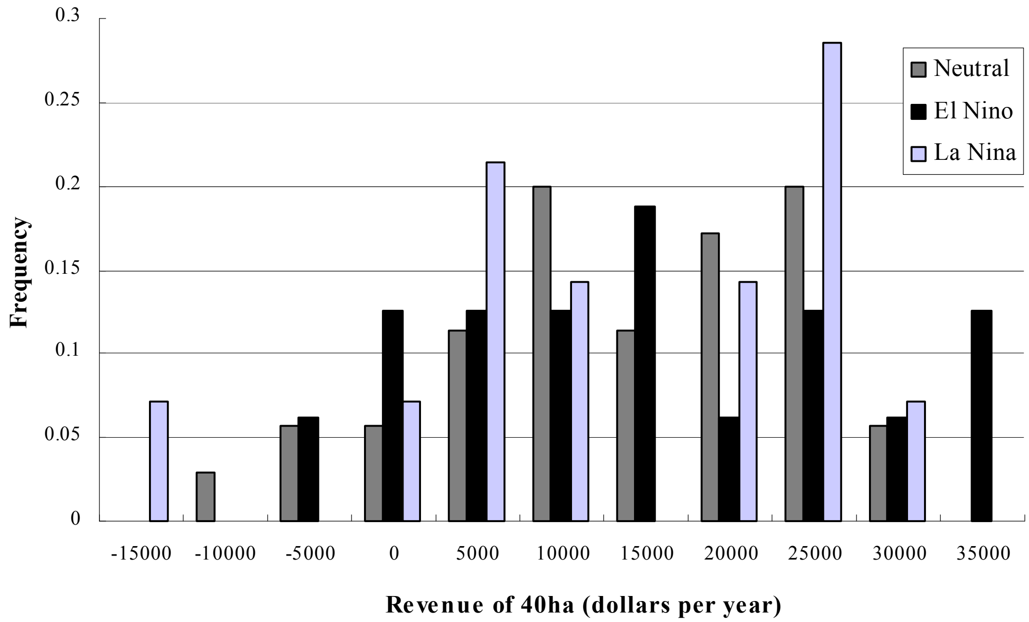

Figure 3: Distribution of optimal income for all ENSO phases without CVaR constraint.

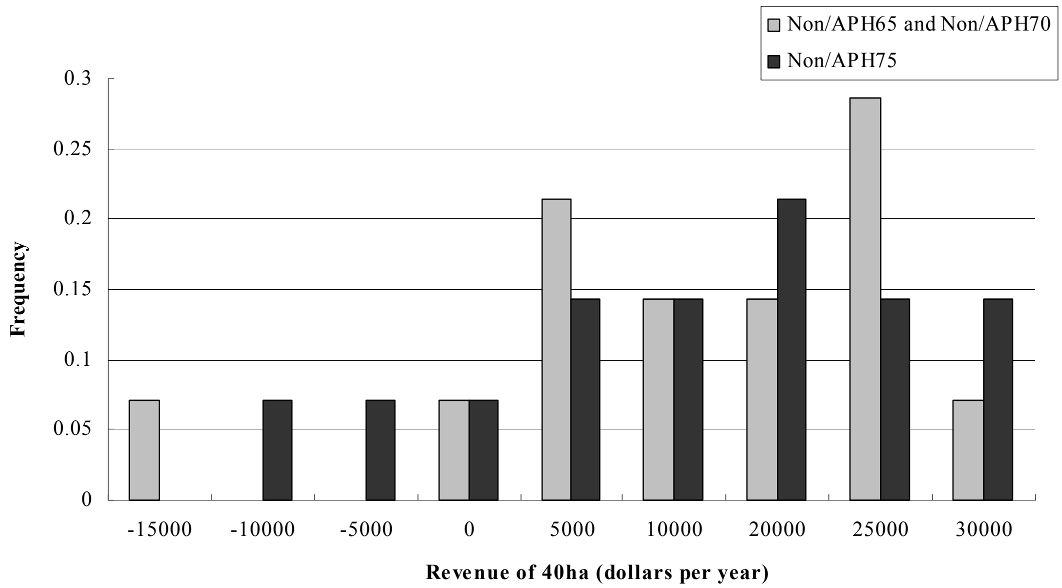

Figure 4: The distribution of optimal revenue for La Niña year under different 95% CVaR limit values.

TABLE 1. Model parameters

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

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

	Peanut	Cotton
APH coverage range (5% increments)	65%-75%	65%-75%
CRC coverage range (5% increments)	N/A	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)	N/A	27.18-288.87
Average yield ($Mg\ ha^{-1}$)	3.362	0.729

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

ENSO Phase	95%CVaR limit v	Expected Revenue	Optimal Insurance Selection	Optimal Planting Date
Neutral	$6,827 and above	$16,250	Cotton: No insurance Peanut: 75%APH	Cotton: April 16th Peanut: May 29th
	Below $6,827	no solution	no solution	no solution
El Niño	$3,717 and above	$17,657	Cotton: No insurance Peanut: 75%APH	Cotton: May 8th Peanut: May 22nd
	Below $3,717	no solution	no solution	no solution
La Niña	$10,624 and above	$16,315	Cotton: No insurance Peanut: 65%APH	Cotton: May 1st Peanut: May 29th
	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