A Game-Theoretic Model of Crop Flood Indemnity in South Florida

Christina Estela Brown
Ph.D. Candidate, Department of Earth & Environment
Florida International University, Miami, Florida
christinaestelabrown@gmail.com

Mahadev G. Bhat
Professor, Department of Earth & Environment, Department of Economics
Florida International University, Miami, Florida
bhatm@fiu.edu

Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

A Game-Theoretic Model of Crop Flood Indemnity in South Florida

Abstract

Crop insurance claims can serve as a metric of the climate-related vulnerability of agriculture. As the expected frequency and intensity of flood and extreme precipitation increases over time, the amount of indemnities paid upon losses due to these events is also expected to increase. This study develops a game-theoretic model of agricultural policy decisions and farmers' optimal response, and places it in the context of the expected effects of climate change on South Florida's precipitation trends. We estimated the optimal per-acre premium for maximum insurance participation for fresh market sweet corn at $126.97 and for fresh market tomatoes at $508.32, both well under the estimated maximum willingness to pay of $325.84 and $969.12, respectively. However, these maximum premium levels are exceeded by per-acre indemnities resulting from the extreme precipitation events occurring during the strongest El Niño years.

Keywords: crop insurance, climate change, crop flood, Florida, Stackelberg game

JEL Classifications: Q54, Q10, Q22, C70

Acknowledgments

This work was partially supported by USDA NIFA Award #2016-38422-25549 and National Science Foundation Grant #EAR-1204762, with additional funding from the Dade County AGRI Council L. Russell Norton Memorial Fellowship.

1. Introduction

Changes in the frequency, spatial distribution, and magnitude of several climatic conditions and extreme events are likely to occur in the not too distant future and could pose significant risks to human well-being (IPCC 2014). Among such changes are an increased potential of flooding due to increased heavy precipitation events and accelerated sea level rise, posing particular concern to coastal communities and agricultural production. South Florida is among the areas of the U.S. most vulnerable to inundation (Gornall et al. 2010; Erwin 2009; Dolan and Walker 2006; Scavia et al. 2002). In addition to inundation, rising sea level can increase salinity of freshwater ecosystems and aquifers (Scavia et al. 2002). A mosaic of urban settlements, agricultural areas, and natural areas, South Florida is served by a highly human-engineered water management system (Harwell et al. 1996). Management agencies grapple with managing water to meet multiple objectives, including urban and agricultural water supply, flood control, and environmental restoration. Climate-induced (e.g., flood, drought, sea level rise) water shortage or excess often tests the limits of this engineering system, and extreme events are in turn expected to further increase the complexity of managing water resources for competing users.

Heavy precipitation and flooding events in the United States and worldwide in recent years have greatly damaged crop production. If model projections of increased weather extremes are realized (National Park Service 2009; IPCC 2014), the cost of crop losses could increase drastically. Recent studies have attempted to simulate the effect of plant damage from excess soil moisture in order to estimate crop production loss, finding that losses under current climatic conditions may double in the next thirty years to an estimated $3 billion annually (Rosenzweig et al. 2002). In 2017, up to 7,000 acres of agricultural land in the southern portions of Florida experienced storm surge with salt water inundation during Hurricane Irma, with the Florida Department of Agriculture and Consumer Services estimating losses at over $30 million (Alvarez 2017)?). The costs of this and other losses may be borne directly by the farmers impacted or transferred to private insurers or governmental disaster relief programs.

As the expected level and intensity of flood and heavy precipitation events increase, the amount of indemnities paid upon losses due to these events would also increase. Thus, crop insurance claims can serve as a metric of the climate-related vulnerability of agriculture. To develop such a metric, it is necessary to study how crop insurance decisions are made. Participation patterns have shifted as new insurance products have expanded farmers' choices of types and levels of coverage, and the literature shows a variety of factors influencing farmers' choices among available crop insurance products (Makki and Somwaru 2001a, 2001b; Sherrick et al. 2004; Smith and Baquet 1996; Moschini and Hennessy 2001). Chief among these factors is the level of risk, followed by the cost of insurance, and the level of premium subsidy. We use a risk-informed decision-based theoretical framework to develop a modeling tool for measuring the impacts of climate-related flooding and excess precipitation.

Frameworks for evaluating farmers' crop insurance decisions typically employ the standard assumption that farmers will maximize the utility of their net revenue subject to physical and technical constraints (Bar-Shira, Just, and Zilberman 1997; Sherrick et al.

2004; Smith and Baquet 1996; Shaik and Atwood 2017; Mahul 1999; Coble and Knight 2002). These studies show that the levels of insurance premium and government subsidy are the two key determinants of farmers' participation. Nevertheless, these two rates are policy decisions made by Risk Management Services (RMS) of USDA each year. RMS grapples with the actuarial decision of optimizing insurance and subsidy rates such that private crop insurers are able to indemnify crop losses year after year adequately. This would require that either premiums, farmers' participation, or both are high enough to generate enough premium income to cover losses. However, farmers' participation level varies inversely with the premium. Furthermore, as the expected level and intensity of flood and heavy precipitation events increase, the amount of indemnities paid upon losses due to these events would also increase. Therefore, ultimate solvency of crop insurance market and climate-related crop risk reduction depend on the interactive decisions of RMS, farmers, and private insurers, under increasing level of climate-induced crop perils. This paper links the occurrence of flooding events and crop insurance indemnity claims by simulating farmers' decision behavior of whether to purchase crop insurance and their choices among alternative products, considering varying risk of perils due to climate change and sea level rise. Government agricultural policy development and farmer response are modeled as a hierarchical Stackelberg leader-follower game-theoretic decision process. In our model, government is assumed to be the dominant player, or leader, choosing an optimal crop insurance premium and subsidy in order to optimize the participation response of the subordinate player, or follower, in this game represented by farmers. Ultimately, this paper seeks to understand the implications of funding insurance subsidies, how subsidy policies can influence participation rates, and setting premium prices for adequate participation by farmers and on private insurers' underwriting ability.

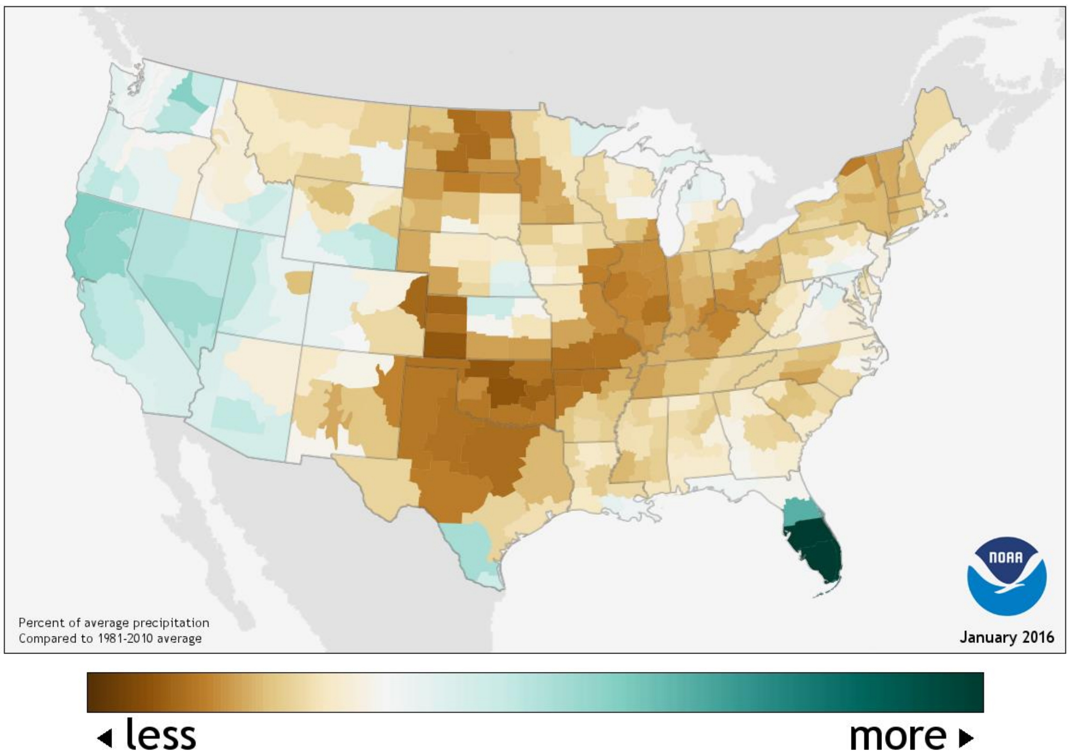
2. Methods

2.1. Delineation of the study area

This study focuses on two crops, fresh market corn and fresh market tomatoes, in Miami-Dade and Palm Beach counties in South Florida. As of 2016, Florida ranked first in value of production of fresh market tomatoes, accounting for 40% of the total U.S. value, and second in value of production of fresh market sweet corn, accounting for 24% of the total U.S. value (Florida Department of Agriculture and Consumer Services 2017). Having a subtropical to tropical climate with a wet (warm) season and a dry (cool) season, cropping season in South Florida for these vegetables typically coincides with the dry season of October through May.

Precipitation patterns in general as well as extreme precipitation events (in South Florida are found to be significantly correlated with large-scale climate effects, including the Atlantic Multidecadal Oscillation (AMO), with a 55-70 year periodicity; the Pacific Decadal Oscillation (PDO), with a 20-30 year periodicity; and the El Niño Southern Oscillation (ENSO), with a 3-7 year periodicity (Gunn 2010; South Florida Water Management District 2011; Wong et al. 2014). During El Niño years, the polar jet stream takes a more southerly flow which allows more frontal systems to reach Florida, increasing precipitation particularly in the dry season (South Florida Water Management District 2011). For the study period of 1989 to 2017, El Niño years are 1991-92, 1994-95, 1997-98, 2002-07, 2009-10, and 2014-16 (NOAA). The 2014-16 El Niño was particularly strong compared to the rest of the US states (Figure 1), leading to nearly $3 million in sweet corn and tomato losses in Miami-Dade and Palm Beach counties.

Figure 1*. Percent of average precipitation compared to 1981-2010 average, January 1996.*



Source: https://www.climate.gov/maps-data/data-snapshots

2.2. Game-theoretic models

Game-theoretic methods, both cooperative and non-cooperative, have been widely used to simulate the strategic behaviors of agents in insurance markets, e.g., natural disaster and crop insurance markets (El-Adaway et al. 2015; Mahul 1999). Hierarchical market solutions, first introduced by Heinrich von Stackelberg in 1934, have in particular been employed to simulate sequential decision-making in situations in which one agent has dominating power over the others (von Stackelberg 1952). Now known as a Stackelberg equilibrium, this sequential game solution concept involves players with asymmetric roles, one a leader and the other following. The leader announces their action and the follower responds by choosing their optimal response given that announcement. The leader, knowing the follower's objective function and anticipating the response, chooses the action that optimizes their own performance given the follower's rational response. Farmers, maximizing their total net revenue, decide whether to participate in the insurance market, and if so, which insurance product to purchase given the price of insurance premium, their risk factors, and a vector of economic variables. Government, knowing farmers' optimal decision, sets the premium and subsidy levels. The farmers' dynamic problem will first be developed, and all necessary conditions derived. These conditions will then be included as constraints in the development of the government's dynamic problem, in which it attempts to balance the income from and flood indemnity claims paid to farmers' insured crops by insurers. Interaction between government and farmers is assumed to be non-cooperative, which can still result in a socially efficient decision strategy under certain possible conditions (Bhat, Alexander, and English 1998). To this end, a sequential hierarchical game becomes particularly relevant for simulating the decision behavior of the government as a price-setter for both premiums and subsidies, and farmers as followers aiming to maximize their profits given the likelihood of perils.

2.2.1 The farmers' model

Farmers' objective is to maximize net revenue from agricultural production (market return less production cost), subject to stochastic peril. Farmers are assumed to lack the ability to influence the government's policy decision once it is made. Alternatively, they attempt to optimally make their decisions regarding insurance purchase in response to the government's decision variable. It is assumed that farmers are price takers and are in a climatologically homogenous region.

Without the purchase of insurance, an individual farmer *n*'s total net revenue (*TR*) is

$$TR = A(1-\theta)R \tag{1}$$

where *A* is planted acres, *R* is net revenue per acre, and θ is the expected probability that a certain peril will occur. With the purchase of insurance, the farmer's *TR* becomes

$$TR_j = A\left[\theta R_j - \left(P_j - S_j\right)\right] \tag{2}$$

where *P* is the cost of insurance premiums, *S* is the subsidy for purchase of insurance, and subindex *j* is the specific insurance product purchased by the farmer. Following the crop insurance decision framework of Sherrick et al. (2004), a farmer will decide to purchase insurance product *j* if their expected *TR* (or utility) with insurance is at least as much as without the insurance. Formally,

$$Prob(yes\ to\ j) = Prob\left\{A\left[\theta R_j - \left(P_j - S_j\right)\right] \geq A(1-\theta)R\right\} \tag{3}$$

The above inequality can be solved for either the farmer's maximum willingness to pay (WTP) for insurance (P_j^*) or the minimum subsidy (S_j^*) a farmer is willing to accept (WTA) to participate in the insurance market. Solving the inequality, the probability that $\left(TR - TR_j\right) \geq 0$ is assumed to yield a linear probability function,

$$Prob(\Delta TR_j \geq 0) = \alpha X \quad (4)$$

where X is a vector of P_j, S_j, M_j, and CCI, and where M represents prior participation and CCI represents general market conditions. Logit and probit models were also considered, and ultimately rejected in favor of a linear probability model using a censored Tobit estimator.

2.2.2 The government's model

With symmetric information, the government, the leader of this game, is assumed to set the price of the premium at the optimal participation price P_j^*, knowing that the farmer-followers will optimally decide their participation rate as in (Eq. 4) in response to the leader's optimal insurance rate decision and given level of subsidy. That is, the leader attempts to set the premium P_j^{**} at a rate that implicitly equates the total premium payment with expected indemnity payment. Formally, P_j^{**} can be determined by solving,

$$C_j P_j - C_j \theta R_j = C_j(P_j - \theta R_j) = 0 \quad (5)$$

Subject to (Eq. 4), where C_j is the extent of area covered by insurance and is a function of $Prob(yes\ to\ j)$, or $Prob_j^*$ and total acres $(\bar{A})$.

That is, $\bar{A}Prob_j^*(yes\ to\ j)(P_j - \theta R_j) = 0$, or,

$$\bar{A}Prob_j^*(P_j, S_j, M_j, CCI)(P_j - \theta R_j) = 0 \quad (6)$$

From (6) above, we can develop a function for the optimal price P_j^{**} which will then determine the optimal participation rates of farmers for insurance product j. Formally,

$$P_j^{**} = \beta_0 + \beta_1 I_{t-1} + \beta_2 CropPrice + \beta_3 RainEvent \quad (7)$$

The final task of this research is to develop a model that captures the relationship between indemnity and farmers' participation level, crop economic variables, government subsidies, and hydro-climatic peril factors. Each individual claim (R_j) is the difference between guaranteed revenue (R) and observed revenue (R_O). That is,

$$Expected\ Claim = I = \int_0^R (R - R_O) f(R_O) dR_O \qquad (8)$$

As R_O is a function of the probability of peril (θ), ultimately, I will become a function of θ. Insurance participation rate for each product *j* is a function of risk factors, government subsidies, expected revenue, and other economic variables. Indemnity then becomes a function of participation rate for each product.

2.3. Estimation of willingness to pay and willingness to accept

Probability of participation was estimated as a censored Tobit model, with a lower limit of 0 and upper limit of 1. Following standard practice (Johnston et al. 2013), the estimates of WTP (P^*) and WTA (S^*) were expressed as the ratios of the attribute coefficients to participation coefficient as in (Eq. 4). Formally,

$$P^* = \frac{\hat{\beta}_0 + \hat{\beta}_2 \bar{S} + \hat{\beta}_3 \bar{M} + \hat{\beta}_4 \widehat{CCI}}{\hat{\beta}_1} \qquad (9)$$

And,

$$S^* = \frac{\hat{\beta}_0 + \hat{\beta}_1 \bar{P} + \hat{\beta}_3 \bar{M} + \hat{\beta}_4 \widehat{CCI}}{\hat{\beta}_2} \qquad (10)$$

Crop insurance and loss data were retrieved from the United States Department of Agriculture (USDA) Risk Management Agency, while crop production and value data were retrieved from the USDA Census of Agriculture. Sourced of weather and climate data include the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information Climate Data Online and NOAA National Weather Service Climate Prediction Center. Data were aggregated into a county-level format for each of the two selected crops, and monthly and annual means were calculated for the study period. All analysis was conducted using Stata13.

3. Results and analysis

3.1 Participation

Results from Tobit model estimations of insurance market participation are described in Table 1. At sample mean levels, estimated likelihood of participation for farmers growing fresh market sweet corn was 0.7523. Estimates for likelihood participation were higher in Miami-Dade County than in Palm Beach County, at 0.7821 and 0.7278, respectively. Farmers growing fresh market tomatoes were approximately half as likely to participate in the insurance market, with overall likelihood at 0.3485. Similarly to sweet corn farmers, Miami-Dade tomato farmers had a higher likelihood of participation than those in Palm Beach, at 0.4041 and 0.2498, respectively.

***Table 1**. Tobit regression results, insurance market participation in Miami-Dade and Palm Beach counties*

	Fresh Market Sweet Corn	**Fresh Market Tomatoes**
Observations	51	45
Log-Likelihood	44.0313	31.5504
Variable	**Coefficient (P-value)**	**Coefficient (P-value)**
Per-Acre Premium	-0.0033 (0.00)	-0.0006 (0.03)
Per-Acre Subsidy	0.0064 (0.00)	0.0012 (0.05)
Previous Year Participation	0.5499 (0.00)	0.7343 (0.00)

Consumer Confidence Index	0.0017 (0.02)	0.0037 (0.00)
Constant	0.1151 (0.30)	-0.3473 (0.02)

Coefficients for premium and subsidy were significant and with expected signs, and for both sweet corn and tomatoes the subsidy coefficient is nearly twice that of the premium, indicating that the level of government subsidy is a stronger driver of insurance purchase decisions than the premium price. The sample mean per-acre premium price for fresh market tomatoes was $444.56, more than quadruple that of fresh market sweet corn ($100.21). Sample mean of subsidy as a percent of premium for sweet corn and tomatoes, deflated to 2017 U.S. dollars, are consistent with national averages for all crops at 55% and 58%, respectively.

For fresh market sweet corn, farmers' maximum WTP for premium was $401.09 in Miami-Dade and $264.03 in Palm Beach, and $325.84 across both counties. Minimum subsidy WTA was $29.77, $86.15, and $60.72 across Miami-Dade, Palm Beach, and both counties, respectively. Farmers of fresh market tomatoes similarly had a higher WTP for premium in Miami-Dade than in Palm Beach, at $1023.35 versus $907.14, and $962.12 overall. Miami-Dade tomato farmers were WTA a minimum subsidy of $91.33, while in Palm Beach the minimum was $0.

3.2 Leader's actuarial premium model estimation

Various model specifications for each fresh market sweet corn and fresh market tomatoes are described in Table 2. The optimal fresh market sweet corn premium estimated at the sample average using Model C2 was $126.79. Using Model T1, the estimated per-acre premium for maximum participation of fresh market tomato farmers was $508.32.

Table 2*. Premium regression results*

Fresh Market Sweet Corn				
	Model C1	**Model C2**	**Model C3**	**Model C4**
Adjusted R Square	0.93	0.87	0.88	0.22
Observations	36	36	36	36
Variable	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**
Intercept		-42.5014 (65.6348)	-36.7346 (61.8134)	-166.8853 (155.1799)
Per-Acre $Indemnity_{t-2}$	0.06236 (0.03778)	0.06248 (0.03814)	0.06207 (0.03755)	0.26203 (0.08745)**
Crop $Price_{t-1}$	0.0384 (0.0080)*	0. 0452 (0. 0132)*	0.04592 (0.0128)**	0.04896 (0.0327)
Extreme Rain $Event_{t-1}$	0.10545 (0.9153)	0.2892 (0.9666)		
$Participation_{t-1}$	53.18154 (21.8593)**	72.8229 (37.5099)**	70.4319 (36.1067)**	126.1255 (91.1857)
County Dummy (PB=1)	-123.7143 (9.683)*	- 123.3320 (9.7931)*	-122.4839 (9.2354)*	
Fresh Market Tomatoes				
	Model T1	**Model T2**	**Model T3**	**Model T4**
Adjusted R Square	0.73	0.74	0.01	0.04
Observations	36	36	36	36
Variable	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**	**Coefficient (Std. Error)**
Intercept			790.0440 (311.0084)**	811.7306 (291.4989)
Per-Acre $Indemnity_{t-2}$	0.1537 (0.0902)***	0.16188 (0.0836)***	0.1138 (0.0796)	0.1081 (0.0743)
Crop $Price_{t-1}$	0.02007 (0.0167)	0.02398 (0.0081)*	-0.0264 (0.02123)	-0.0266 (0.0209)
Extreme Rain $Event_{t-1}$	2.4297 (9.0430)			
$Participation_{t-1}$	104.85 (174.2490)	93.67687 (166.7427)	-57.4941 (165.2168)	-76.3857 (140.5113)
County Dummy (PB=1)	80.6564 (97.4179)	89.0560 (90.9182)	20.0152 (88.3249)	

**p<.01, **p<.05, ***p<.10*

Maximum WTP and minimum WTA were estimated for premium and subsidy, respectively, for each county individually as well as for sweet corn and tomatoes overall and are described in Table 3. At the maximum WTP for insuring sweet corn, there is only one crop year, 2010, in which per-acre indemnity exceeds the per-acre premium (Figure 2). For tomatoes, the per-acre indemnity twice exceeds the maximum per-acre premium, in 2002 and 2012 (Figure 3).

Table 3. *Maximum premium WTP and minimum subsidy WTA for participation in crop insurance market, 2017 US $*

	Overall	**Miami-Dade**	**Palm Beach**
Fresh Market Sweet Corn			
Maximum premium WTP	$325.84	$401.09	$264.03
Minimum subsidy WTA	$60.72	$29.77	$86.15
Fresh Market Tomatoes			
Maximum premium WTP	$969.12	$1023.35	$907.14
Minimum subsidy WTA	$30.06	$91.33	$0

3.2 Policy and climate simulations

The U.S. Government Accountability Office (2014) found that reducing premium subsidies could potentially save hundreds of millions of dollars in the federal budget, Tables 4 and 5 illustrate the effects this action would have on participation rates. Holding per-acre premium prices constant, reducing subsidies by 20% lowers participation from 75% to 68% and from 35% to 28% for sweet corn and tomatoes, respectively, at the highest level of reduction (Table 4). Nearly all years in which per-acre indemnity exceeds per-acre premiums coincide with occurrences of El Niño (Figures 2 and 3).

Table 4. *Participation at various levels of subsidy reduction (Fresh Market Sweet Corn), 2017 US $*

Fresh Market Sweet Corn				
% Reduction in subsidy	**5%**	**10%**	**15%**	**20%**
$/acre Reduction in subsidy	*2.77*	*5.54*	*8.32*	*11.09*
New subsidy per acre	$52.71	$49.94	$47.16	$44.39
Participation rate	0.734367	0.716406	0.698445	0.680484

Table 5. *Participation at various levels of subsidy reduction (Fresh Market Tomatoes), 2017 US $*

Fresh Market Tomatoes				
% Reduction in subsidy	**5%**	**10%**	**15%**	**20%**
$/acre Reduction in subsidy	*12.94*	*25.89*	*38.84*	*51.79*
New subsidy per acre	$246.04	$233.09	$220.14	$207.19
Participation rate	0.33291	0.317296	0.301683	0.286069

Figure 2. *Per-acre indemnity vs. premium, Fresh Market Sweet Corn 1990-2017*

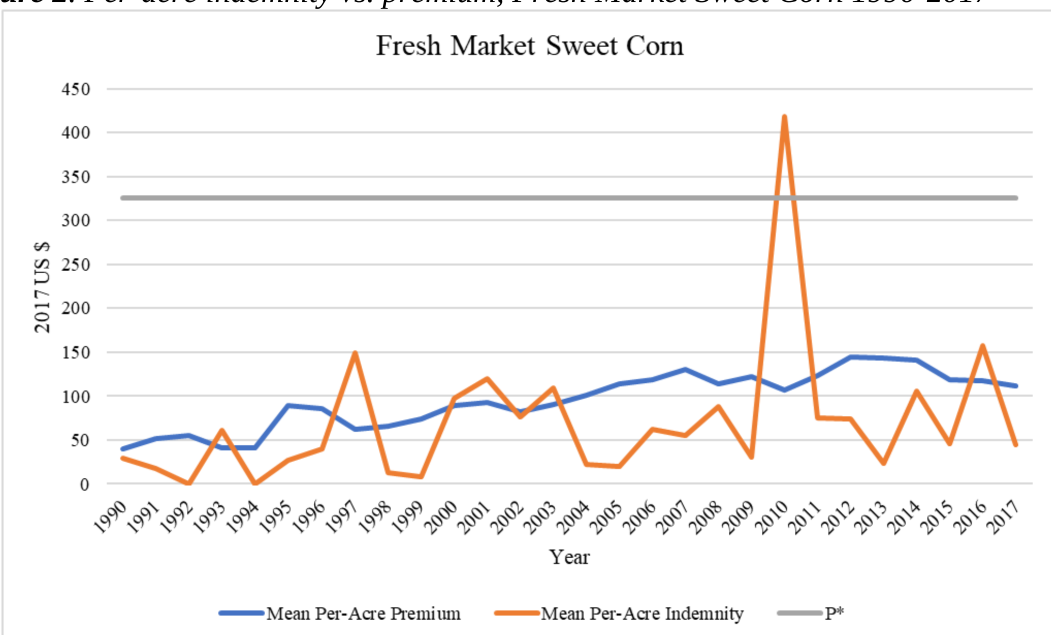
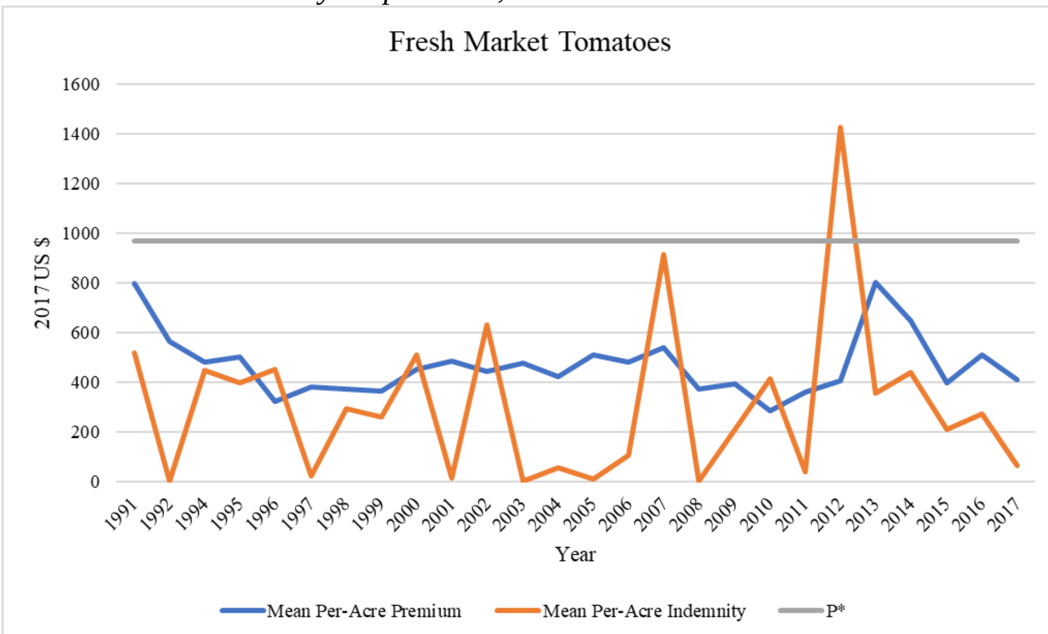


Figure 3. *Per-acre indemnity vs. premium, Fresh Market Tomatoes 1991-2017*



Conclusions and future work

The existing literature primarily looked at farmers' participation behavior (i.e., response to insurance premium or subsidy), without looking at the policymaker's decision. Our paper is the first to capture the simultaneity of farmers' and government decisions through a hierarchical strategic leader-follower game model. Farmers' crop insurance participation decision was driven mainly by prior participation and the levels of premium and subsidy. The government's decision was affected by participation levels, crop price, prior indemnity, and peril, and varied by county. The models yielded optimal WTP for premium and WTA for subsidy, which have been above the government-set premium rates.

Actual indemnities from flood and excess moisture have exceeded crop premiums in several years, and WTP in one year. This demonstrates that the government has to be cautious in setting premiums in response to expected perils. Any government decision to reduce subsidies may adversely affect the farmers’ decisions and destabilize the overall crop insurance market.

A trend analysis by the South Florida Water Management District (2011) from 1950-2008 shows a general decrease in wet season precipitation, possibly due to a shortening or delay of the wet season, but an increase in the number of wet days during the dry season. Coupled with sea level rise and the attendant need for flood control, a series of strong El Niño years could prove catastrophic not only for farmers but for insurers. Reductions in subsidies may also negatively impact insurers. As subsidy rates decline, so do the corresponding participation rates for a given insurance product. Based on the results of this study, the authors will develop the model further to consider other climatic factors, as well as expand the study area geographically and in terms of agricultural and insurance products.

References

Alvarez, Sergio. 2017. "Hurricane Irma's Damage to Florida Agriculture." http://www.freshfromflorida.com/content/download/77515/2223098/FDACS+Irma+Agriculture+Assessment.pdf.

Bar-Shira, Z, R E Just, and D Zilberman. 1997. "Estimation of Farmers' Risk Attitude: An Econometric Approach." *Agricultural Economics* 17: 211–22. http://ageconsearch.umn.edu/record/174314/files/agec1997v017i002-003a009.pdf.

Bhat, Mahadev G., Robert R. Alexander, and Burton C. English. 1998. "Toward Controlling Nonpoint Source Pollution of Groundwater: A Hierarchical Policy Formulation Game." *Natural Resource Modeling* 11 (4): 379–403. doi:10.1111/j.1939-7445.1998.tb00316.x.

Coble, Keith H., and Thomas O. Knight. 2002. "Crop Insurance as a Tool for Price and Yield Risk Management." In *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture*, 445–68. Boston, MA: Springer US. doi:10.1007/978-1-4757-3583-3_20.

Dolan, A. H., and I. J. Walker. 2006. "Understanding Vulnerability of Coastal Communities to Climate Change Related Risks." *Journal of Coastal Research* 3 (SI 39): 1316–23. doi:10.2307/25742967.

El-Adaway, Islam, Kalyn Coatney, Mohamed S Eid, ; Islam, H El-Adaway, M Asce, and Kalyn T Coatney. 2015. "Evolutionary Stable Strategy for Postdisaster Insurance: Game Theory Approach." *Article in Journal of Management in Engineering*. doi:10.1061/(ASCE)ME.1943-5479.0000357.

Erwin, Kevin L. 2009. "Wetlands and Global Climate Change: The Role of Wetland Restoration in a Changing World." *Wetlands Ecology and Management* 17 (1): 71–84. doi:10.1007/s11273-008-9119-1.

Florida Department of Agriculture and Consumer Services. 2017. "2016 Florida Agriculture by the Numbers." https://www.nass.usda.gov/Statistics_by_State/Florida/Publications/Annual_Statistical_Bulletin/FL_Agriculture_Book/2016/Florida_Agriculture_by_the_Numbers_Brochure_2016.pdf.

Gornall, Jemma, Richard Betts, Eleanor Burke, Robin Clark, Joanne Camp, Kate Willett, and Andrew Wiltshire. 2010. "Implications of Climate Change for Agricultural Productivity in the Early Twenty-First Century." *Philosophical Transactions of the Royal Society of London B: Biological Sciences* 365 (1554): 2973–89. doi:10.1098/rstb.2010.0158.

Gunn, Angus M. 2010. "Chapter 20: Climate and Weather Extremes." *The Future of the World's Climate*, 575. doi:10.1016/B978-0-12-386917-3.00010-5.

Harwell, M A, J F Long, A M Bartuska, J H Gentile, C C Harwell, V Myers, and J C Ogden. 1996. "Ecosystem Management to Achieve Ecological Sustainability: The Case of South Florida." *Environmental Management* 20 (4): 497–521. doi:Doi 10.1007/Bf01474652.

IPCC. 2014. "Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." Edited by Core Writing Team, R K Pachauri, and L A Meyer.

IPCC.

Johnston, Robert J., Eric T. Schultz, Kathleen Segerson, Elena Y. Besedin, and Mahesh Ramachandran. 2013. “Stated Preferences for Intermediate versus Final Ecosystem Services: Disentangling Willingness to Pay for Omitted Outcomes.” *Agricultural and Resource Economics Review* 42 (1): 98–118.

Mahul, O. 1999. “Optimum Area Yield Crop Insurance.” *American Journal of Agricultural Economics* 81 (1). Oxford University Press: 75–82. doi:10.2307/1244451.

Makki, Shiva S, and Agapi Somwaru. 2001a. “EVIDENCE OF ADVERSE SELECTION IN CROP INSURANCE MARKETS.” ©*The Journal of Risk and Insurance* 68 (4): 685–708. https://pdfs.semanticscholar.org/6b04/0846cd1a3b05e9239d7bb20f0924301a2b36.pdf.

———. 2001b. “FARMERS’ PARTICIPATION IN CROP INSURANCE MARKETS: CREATING THE RIGHT INCENTIVES.” *Amer. J. Agr. Econ* 83 (3): 662–67. http://www.jstor.org/stable/pdf/1245096.pdf?refreqid=excelsior:934f441915c36b6b6363576074558863.

Moschini, Giancarlo, and David A Hennessy. 2001. “Agricultural Production: Uncertainty, Risk Aversion, and Risk Management for Agricultural Producers.” *Handbook of Agricultural Economics* 1. Elsevier Science Publishers: 88–153. doi:10.1016/S1574-0072(01)10005-8.

National Park Service. 2009. “Potential Ecological Consequences of Climate Change in

South Florida and the Everglades: 2008 Literature Synthesis.” Homestead, Florida.

Rosenzweig, Cynthia, Francesco N. Tubiello, Richard Goldberg, Evan Mills, and Janine Bloomfield. 2002. “Increased Crop Damage in the US from Excess Precipitation under Climate Change.” *Global Environmental Change*. doi:10.1016/S0959-3780(02)00008-0.

Scavia, Donald, John C Field, Donald F Boesch, Robert W Buddemeier, Virginia Burkett, Daniel R Cayan, Michael Fogarty, et al. 2002. “Climate Change Impacts on US Coastal and Marine Ecosystems [Review].” *Estuaries* 25 (2): 149–64. doi:10.1007/BF02691304.

Shaik, Saleem, and Joseph Atwood. 2017. “ESTIMATING THE DEMAND OF CROP INSURANCE AND SUPPLY OF INDEMNITY PAYMENTS: NEBRASKA AGRICULTURE SECTOR.” Accessed August 15. http://ageconsearch.umn.edu/bitstream/21795/1/sp00sh01.pdf.

Sherrick, Bruce J, Pierre J Barry, Paul N Ellinger, and Gary D Schnitkey. 2004. “Factors Influencing Farmers’ Crop Insurance Decisions.” *American Journal of Agicultural Economics* 86(1) (1). Oxford University Press: 103–14. http://www.jstor.org/stable/3697877.

Smith, V. H., and A. E. Baquet. 1996. “The Demand for Multiple Peril Crop Insurance: Evidence from Montana Wheat Farms.” *American Journal of Agricultural Economics* 78 (1). Oxford University Press: 189–201. doi:10.2307/1243790.

South Florida Water Management District. 2011. “Past and Projected Trends in Climate and Sea Level for South Florida.”

Stackelberg, Heinrich von. 1952. *The Theory of the Market Economy*. Hodge. https://books.google.com/books/about/The_theory_of_the_market_economy.html?id=8wOlnQAACAAJ.

United States Government Accountability Office. 2014. "Crop Insurance: Considerations in Reducing Federal Premium Subsidies Considerations in Reducing Federal Premium Subsidies What GAO Recommends." https://www.gao.gov/assets/670/665267.pdf.

Wong, P.P., Ij Losada, J-p Gattuso, J Hinkel, A Khattabi, KL McInnes, Y Saito, and A Sallenger. 2014. "Coastal Systems and Low-Lying Areas." In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 361–409. Cambridge University Press.