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Farm-Level Risk Management Using Irrigation and Weather Derivatives

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An agronomic crop growth model—the Decision Support System for Agro-Technology Transfer—and a constant relative risk aversion utility function are used to examine corn irrigation strategies in Mitchell County, Georgia. Precipitation contracts are designed to help farmers manage risk. Three conclusions originate from the findings. First, the optimal irrigation strategy can greatly increase producers' certainty-equivalent revenue. Second, changes in water pricing policy would have a limited impact on the amount of water used. And third, across levels of risk preference, the precipitation contracts are not effective in increasing certainty-equivalent revenue or reducing cumulative water use.

Key Words: irrigation risk management, water pricing policy, weather derivative contract

JEL Classifications: D8, G22, Q15, Q25

Agricultural production has always been a risky endeavor, with stochastic weather conditions affecting farm production and revenue, and irrigation has been identified as an important risk management strategy (Boggess et al.). In Georgia, although annual rainfall is adequate for most agricultural crops, the distribution of rainfall across a year is highly unpredictable. Irrigation is extensively used in Georgia to offset the impact of rainfall variability on crop yield and to reduce the risk associated with weather variability.

Recently, water scarcity has become a social and economic concern for policymakers in Georgia. Since irrigated agriculture has historically represented the largest consumptive use in the state, a comprehensive water policy for Georgia's future must address agricultural water demand. Simulation tools provide the opportunity to analyze water use efficiency and its impact on water scarcity (Morgan, Biere, and Kanemasu). Several studies have examined on-farm irrigation using the engineering notion of irrigation water (i.e., the ratio of water stored in the crop root zone to the total water diverted for irrigation) and have found opportunities for water savings while increasing yield (e.g., Harris and Mapp 1980, 1988; Howell, Hiler, and Reddell; Lyle and Bordovsky; Raju et al).

While engineering studies have addressed the changes and the diffusion of irrigation technologies in agriculture, they often lack economic intuition. The decision environment is typically nonoptimizing—with the exception of yield maximization—and the issue of risk is rarely considered.

In the financial world, new insurance instruments (catastrophe options, weather derivative contracts, and so on) are being developed to improve farmers' risk management options (Miranda and Vedenov). There are currently markets for temperature-based weather derivatives traded on the Chicago Mercantile Exchange as well as more personal markets for over-the-counter weather derivatives exchanged in the form of weather swaps

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and options (Forrest). While the market for weather derivatives based on temperature indices has grown significantly, the market for precipitation-based derivatives is still in its infancy, making it a natural area for further research (Varangis, Skees, and Barnett).

The primary objective of this paper is to present a theoretical framework of irrigation water decisions when weather derivatives are available. The framework is then applied to corn production in southwest Georgia. The application illustrates the impact of both water price and risk preferences on the financial parameters defining the optimal weather derivative as well as their impact on expected water applications.

Literature Review

Advances in the understanding of the physical, chemical, and biological environment of the soil–plant– atmosphere continuum and environmental monitoring technology offer us the opportunity to base crop performance and assessment on sound scientific principles (Jagtap et al.). A number of studies have used simulation models to evaluate irrigation schedules based on plant growth relationships (e.g., Harris and Mapp; Howell, Hiler, and Reddell; Lyle and Bordovsky). The primary contributions of these studies have been improved specifications of the agronomic relationships describing the irrigation–plant growth environment and incorporation of multiple crops into the decision framework.

For example, Zavaleta, Lacewell, and Taylor use the grain sorghum growth model by Maas and Arkin to consider stochastic weather and allow irrigation timing and quantity decisions to be based on an expected profit maximization criterion. Numeric search procedures, referred to as open-loop stochastic control, are used to derive irrigation strategies that maximize expected profits over eight discrete irrigation periods of the crop year.

Harris and Mapp (1988) use the same grain sorghum plant growth model to analyze intensive and water-conserving irrigation strategies. A number of irrigation strategies are simulated with their modifications to the plant growth model. Stochastic dominance procedures are used to identify risk efficient irrigation strategies.

Endale and Fipps apply the Irrigation District Decision Support System, a crop growth and irrigation district simulation model capable of predicting biomass development and yields for fields varying in soil type and irrigation management scenarios, to a large irrigation scheme in the Middle Awash Valley of Ethiopia. Crop yields are simulated over a 12-year period to determine which of 12 separate irrigation schedules in use meet the objectives of maximizing yields or minimizing water use. Their results illustrate the potential role of decision support systems in the evaluation and management of large irrigation projects.

Apart from irrigation, farmers also choose insurance products to improve their risk profile (Schnitkey, Sherrick, and Irwin). The flexibility of defining weather indices allows innovative structures to be developed using these instruments to manage a wide variety of weather-related risks (Mahul). Sellers of weather derivatives usually include major energy companies that use the instruments to hedge their own risks and to make trading profits. Insurance and reinsurance companies are also important providers of capacity as they look for alternative ways to deploy their capital. Weather derivatives appeal to a wide array of investors as an uncorrelated asset class.

Richards, Manfredo, and Sanders found that a temperature-based weather index insurance product could be used to offset production risks faced by nectarine growers in Fresno County, California. Skees et al. found that a rainfall index insurance scheme could be feasible in Morocco and Argentina. Turvey examined the economics and pricing of weather index insurance in Ontario and suggested that temperature and precipitation-based insurance contracts could be used to insure against yield losses for some crops. Vedenov and Barnett investigated the feasibility of using weather index insurance to protect against shortfalls in corn and soybean yields in Iowa and Illinois and cotton yields in Mississippi and Georgia.

Methodology

In order to study the decision problem of a risk-averse competitive agricultural producer under output price and weather risks, we used an expected utility maximizing model. The objective was to maximize the expected value of a von Neumann–Morgenstern utility function of profit $u(\pi)$, with $u' > 0$ and $u'' < 0$. As empirical studies have demonstrated that farmers in many areas exhibit decreasing absolute risk aversion (Escalante and Rejesus), that is,

$$R_a'(y) = \frac{-u'''u' + u''^2}{u'^2} < 0$$

given that $u' > 0$, $u'' < 0$, a necessary condition for decreasing absolute risk aversion is $u''' > 0$.

A widely used representation of expected utility that satisfies the maintained hypothesis of $u' > 0$, $u'' < 0$, and $u''' > 0$ is the constant relative risk aversion utility function that is best parameterized as

$$(1) \qquad U = \frac{R^{1-\xi}}{1-\xi},$$

where R is the return to the decision maker and ξ is the relative risk aversion coefficient. This model is employed in this paper to examine irrigation strategies and precipitation contract design across different levels of risk aversion coefficients.

Expected farm yield, revenues and costs for various irrigation strategies were generated by the Decision Support System for Agro-Technology Transfer (DSSAT). We were then able to identify the plant-available water threshold that maximized the expected utility function.

Certainty-equivalent revenues (CERs) were used to assess the robustness of the risk reduction performance of the optimal irrigation and precipitation contract (Manfredo and Leuthold). For a specified utility function, CER is the level of return that, if received with certainty, would generate a level of utility equal to the expected utility of the risky investment. While it allows for consideration of higher moments of the return distribution, CER also requires one to make assumptions about the decision maker's utility function over returns (Chen, Roberts, and Thraen). Using the utility function in Equation (1), the CERs can be calculated as

$$(2) \qquad CER = ((1-\xi)(EU(R))^{\frac{1}{1-\xi}}.$$

The critical components in the precipitation contract design involve setting the indemnity payments and the premium of the contract. Indemnity refers to the payments made to the holder of the contract when events as specified in the contract trigger a payment. The proposed insurance product would function much like a put option on precipitation. In particular, the precipitation contract envisaged here is designed to trigger a payment when rainfall in the said time period falls short of a certain set strike rainfall amount. The indemnity is paid conditional on the realization of the precipitation according to the following schedule:

$$(3) \qquad f(i|x,i^*,\lambda) = x \times \begin{cases} 0 & i > i^* \\ \dfrac{i^* - i}{i^* - \lambda i^*} & \lambda i^* < i \le I^*, \\ 1 & i \le \lambda i^* \end{cases}$$

where $f(i|x, i^*, \lambda)$ is the indemnity, i is the rainfall index for a specific period measured not at the farm as in Equation (3) (in the crop simulation model) but rather at the weather station referenced in the insurance contract, i^* is the strike, and x is the maximum indemnity. The contract triggers an indemnity whenever i falls below i^*, and the maximum indemnity x is paid whenever the index falls below the limit $\lambda^* i$. Thus, the contract can be uniquely identified by fixing the three parameters i^*, λ, and x.

The premium on the precipitation standard contract is a function of i^*, λ, x and the probability distribution of i. The distribution can be estimated based on historical precipitation data either by fitting a standard parametric distribution or by using a non-parametric approach such as kernel smoothing. For this study, kernel smoothing is used to derive a continuous probability density function $h(i)$ of i. Formally, for index realizations i; $t = 1, \ldots, T$, the kernel density function of the index is calculated as

$$(4) \quad h(i) = \frac{1}{T\Delta}\sum_{t=1}^{T} K\left(\frac{i - i_t}{\Delta}\right),$$

where $K(\cdot)$ is a kernel function, and Δ is a degree of smoothness or bandwidth (Härdle). The expected payoff and hence the actuarially fair premium for the standard contract can be determined by

$$(5) \quad \begin{aligned} \pi_{fair}(x,i^*,\lambda) &= \int (i|x,i^*,\lambda)h(i)di \\ &= x\int_0^{\lambda i^*} h(i)di + x\int_{\lambda i^*}^{i^*} \frac{i^* - i}{i^*(1-\lambda)}h(i)di. \end{aligned}$$

This formulation for calculating the pure premium is based on the pure loss cost history and does not cover the transaction costs or risk preference of partners. Reinsurance firms usually load the pure premium based on the variance of the loss costs. If one further assumes that a proportional premium load $\gamma(\gamma \geq 0)$ is applied to the actuarially fair premium to cover transaction costs, return on investment, and reserve building, then the loaded premium is

$$(6) \quad \pi_{loaded}(i^*,\lambda,\gamma) = (1+\gamma)\pi_{fair}.$$

For the purposes of this study, a 10% load is imposed on the standard deviations of indemnity payments per liability. Using the previous procedure, preliminary estimates for indemnity payments, pure premium rates, and loaded premium rates (the ratio of premium to maximum liability) for Mitchell County can be arrived at given strike, limit, and liability.

The irrigation cost during the worst years is considered a good proxy for the value at risk and used to establish a liability estimate by crop. Strikes are selected as the levels of precipitation at which the predicted yields are equal to the corresponding longtime average; that is, the contracts are designed to pay at least some indemnity whenever predicted yields dropped below the average. Similar index insurance contract designs are presented in Martin, Barnett, and Coble. The remaining parameters for the contract are the strikes i^* and limit parameter λ, which can be solved as follows.

Suppose a producer values investment returns according to maximizing the expected value of the previously mentioned utility function. Further suppose a representative producer's investment portfolio consists only of irrigation application and precipitation contracts. The mathematical formulation of the farm level model is as presented here:

$$(7) \quad \begin{aligned} Max(EU) &= \frac{1}{25}\sum_{t=1976}^{2000}\big[(NR_{without})_t \\ &\quad + f_t(i_t|x,i^*,\lambda) \\ &\quad - \pi(x,i^*,\lambda)\big]^{1-\xi} \\ &\quad \div 1-\xi \\ &= \frac{1}{25}\sum_{t=1976}^{2000}\Big[\big(qP_{crop} - wC_{pumping}\big)_t \\ &\quad + f_t(i_t|x,i^*,\lambda) \\ &\quad - \pi(x,i^*,\lambda)\Big]^{1-\xi} \\ &\quad \div 1-\xi, \end{aligned}$$

where E denotes the expectation operator, $NR_{without}$ denotes net return to an irrigated farm without weather derivative contract for a specific year t, $C_{pumping}$ denotes per unit irrigation cost, w denotes irrigation amount, q denotes crop yield, P denotes crop price, f_t denotes instrument payoff (indemnity) for year t, π is contract premium, and A denotes relative risk aversion coefficient.

The decision variables, namely, the strike, the limit parameter λ, and irrigation amount w, are selected for each analysis unit so as to maximize the expected utility function over a historic period (1976–2000). Once the contract parameters strike, liability and limit are solved, and indemnity payments and premium rates can be formulated.

Data

The DSSAT crop growth model utilizes crop management data, daily weather data, and soil data. The economic model requires output price data and crop management cost data.

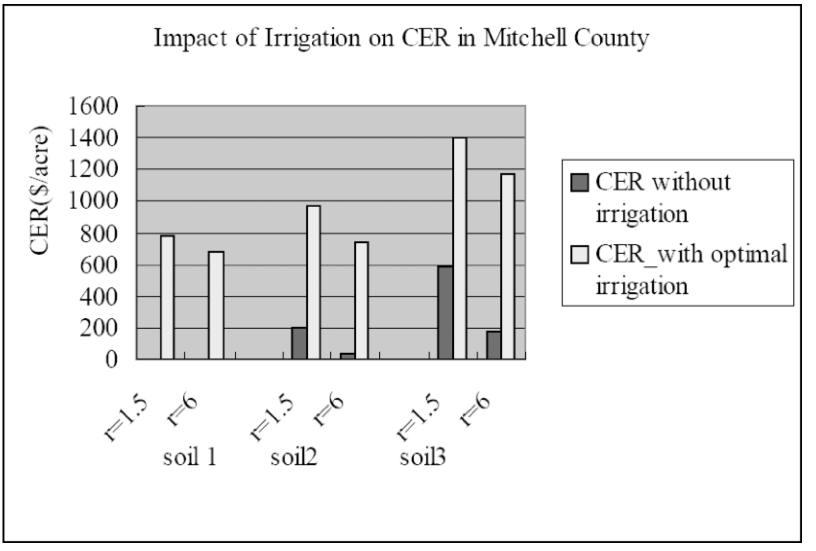

Figure 1. Impact of the Optimal Irrigation on Producers' Certainty Equivalent Revenue for Corn Production in Mitchell County

Daily weather data are available from the U.S. National Climate Data Center. Evapotranspiration rates are calculated from daily weather data using Priestley–Taylor methods. The climate data can be plotted or tabulated and saved as a prm climate file. Soil information came from the University of Georgia's Agricultural Economics Extension Program. Three common soil types in Georgia (Norgram Sandy Soil, Tifton Loamy Sand, and Norfolk Loamy Sand) are included in the study.

Results

The results are organized as follows. The first section provides evidence that irrigation is a viable tool in farm-level risk management and analyzes the impact of water pricing policy on expected water use. Regional estimates for the precipitation insurance are developed for the study area. The third section provides analysis on the impact of the precipitation contract on irrigation decision and risk management.

Irrigation in Farm-Level Risk Management

Figure 1 shows the impact of the optimal irrigation strategy on producers' CER for corn production in Mitchell County. From this graph, we can see that the CER of the optimal irrigation ranges from two to nearly five times the CER for dryland production. Across all soil types and risk aversion levels, irrigation is shown to be an effective risk management tool for corn production.

The impact of water price on expected water use is shown in Figure 2. This graph indicates that water application rates that maximize expected utility are independent of water price and risk aversion coefficients over wide ranges. Soil type, however, does have an impact on expected water use.

Regional Estimates for Precipitation Contracts

Table 1 present optimal combinations of i^* and λ for three soil types in Mitchell County. These are the combinations that yield the largest expected utility for a specific risk aversion level ξ. The variety of indices and contract types presented from Table 1 indicates that weather derivatives cannot be designed in a one-size-fits-all manner, even for the same crop within the same area.

The optimal strike is much smaller than the average precipitation, resulting in 0 payoff in most of years, and thus the fair premium is 0. The probability of triggering a payment for Mitchell County is very low. This is why the premium rate on the contract is also very low.

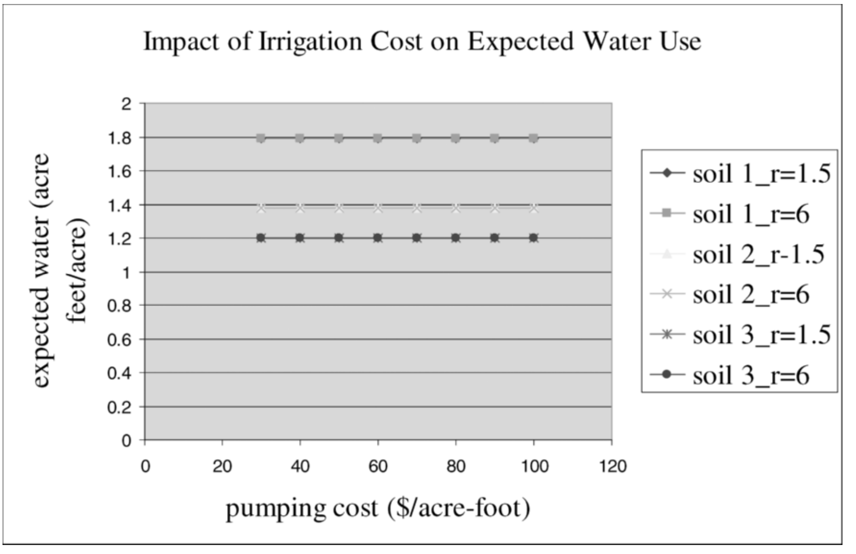

Figure 2. Impact of Potential Water Pricing Policy on Producers' Optimal Water Use for Mitchell County

As indicated in Table 1, the premium rates associated with the weather contracts turned out to be low, ranging from 1.4% to 2.8% of maximum liability for both risk aversion levels.

Impact of Precipitation Contract on Irrigation and Risk Management

Table 2 presents changes in producers' irrigation decision from purchasing precipitation insurance as well as changes in producers' well-being as measured by CER. The CER are calculated using i^* and λ from Table 2 for $r = 6$ and $r = 1.5$, respectively. From the table, we can see that a weather derivative based on rainfall does not change a producer's irrigation decisions for any soil type, regardless of the level of risk aversion. Unexpectedly, risk-averse corn producers in Mitchell County are not generally made better off by purchasing rain-based insurance contracts. The optimal strikes are much lower than the expected rainfall during the growing season, making the indemnity each year very low, and leads to low fair premium and loaded premium rates. As a result, producers gain little from buying weather derivative contracts each year, and the 10% proportional load only increases their cost. If the weather derivative contract is applied on nonirrigated crops, it may increase producers' utility because of its role in variance reduction, but in our case, with irrigation application, the variance of profits during the 25 years is already much lower than that for nonirrigated crops.

Table 1. Contract Parameters for Corn Production in Mitchell County

Soil	r	max_liability	expected_rain	Strike	Limit	Tick	premium_rate
1	1.5	700.03	564.76	132	0.76	7.56	0.01447
1	6	700.03	564.76	132	0.76	7.56	0.01447
2	1.5	512.12	564.76	132	0.84	7.14	0.02162
2	6	512.12	564.76	132	0.84	7.14	0.02162
3	1.5	471.82	564.76	132	0.77	3.78	0.02775
3	6	471.82	564.76	132	0.77	3.94	0.02775

r is relative risk aversion level; max_liability is maximum liability.

Table 2. Optimal Contract Design and Irrigation Decision for Corn Producers in Mitchell County

Soil	r	CER_w/	EW_w/	moi_w/	CER_w/o	EW_w/o	moi_w/o	ΔCER	ΔEW
1	1.5	773	1.78	25	784	1.78	25	−11	0
1	6	671	1.78	25	682	1.78	25	−12	0
2	1.5	956	1.39	65	967	1.39	65	−11	0
2	6	723	1.39	65	736	1.39	65	−13	0
3	1.5	1,397	1.20	30	1,407	1.20	30	−11	0
3	6	1,153	1.20	30	1,167	1.20	30	−13	0

r is relative risk aversion level; CER_w/ is certainty equivalent revenue with contract; EW_w is expected water use with contract; moi_w is soil moisture target with contract; CER_w/o is certainty equivalent revenue without contract; EW_w/o is expected water use without contract; moi_w/o is soil moisture target without contract; ΔCER is change in certainty equivalent revenue; and ΔEW is change in expected water.

Conclusions

Crop simulation models offer new opportunities to explore potential impacts of water policy and financial instruments on farm welfare. We used the DSSAT model to simulate yield, revenue, and irrigation cost responses to various irrigation strategies over 25 years. Our analysis provides evidence that irrigation is an important risk management strategy for corn production in Georgia. However, because of the supplemental nature of irrigation in the state, optimal water application rates for corn appear to be largely independent of water price and risk aversion levels.

Given the recent rise in corn prices, irrigated corn acreage in Georgia is expected to increase substantially in 2008. This could have a significant impact on water withdrawals, especially if the current drought continues, as expected. Our analysis suggests water price adjustments would do little to dampen water demand on corn acres. This conclusion appears to hold even if rain-based insurance contracts were available.

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