Spatial and Temporal On-Farm Risk Management - Crop Production Scheduling and Index Insurance Strategies

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Abstract

An agronomic crop growth model, Decision Support System for Agro-Technology Transfer (DSSAT), is used to find optimal crop management strategies for cotton production in Mitchell, Miller, and Lee Counties in Georgia during the past 10 years. Planting date and irrigation threshold are the two variables optimized to maximize farmer's expected utility. A decreasing absolute risk aversion - constant relative risk aversion (DARA-CRRA) utility function is used to examine crop management decision that can be influenced by changes in inter-temporal risk behavior. Comparison is made from management perspective - one is dynamic crop management strategy that varies each year; one is static (constant) strategy over 10 years. Based on the best crop management strategies, index insurance products are designed to help farmers further reduce production risk. The impact of geographical basis risk was assessed by comparing the risk reduction generated from index insurance contracts based on different weather stations; the impact of temporal basis risk is assessed by allowing separate contracts to be purchased for different sub-periods during the entire period.

Key Words: Irrigation, Planting Date, Risk Management, Weather Derivative Contract, Basis Risk

Introduction

Agricultural production has always been a risky endeavor. The inherent biophysical nature of agricultural systems combined with the various external stimuli (e.g., economics) makes it vulnerable to various sources of risk. Two primary risks are market risk and production risk. The market risk is in terms of price variation resulting from the market supply and demand changes. The production risk addressed is in terms of variability of crop yield due to spatial and temporal weather, which includes extreme rainfall or temperature events as well as natural disasters. Weather conditions greatly affect the production of farmers and therefore their revenue.

Spatial and temporal variability of crop factors within a field can have a significant influence on agricultural production by reducing yield and quality of produce. Water commonly has a leading role among the factors responsible for spatial and temporal yield variability and is a major input resource for precision management. Soil water relations have been shown to explain more than 50% of infield yield variability (Howell et al.). Temporal and spatial management of soil water can significantly increase water use efficiency (Jagtap et al.).

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. In addition to water application scheduling, selecting the best planting date is another critical decision growers must make to enable a crop to have a successful start.

Simulation tools provide the opportunity to provide producers with better crop production scheduling (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 Mapp1980; Harris and Mapp1988; 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, the federally subsidized crop insurance program provides crop producers with protection against many weather-related risks. However, the program is plagued with moral hazard and adverse selection problems (Skees et al). In contrast, index crop insurance products can eliminate the asymmetric information problem inherent in farm-level multiple peril crop insurance. In addition, with index insurance products, there is no need for farm-level loss adjustment so transaction costs are low.

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 and options. Weather derivatives are typically based on official NOAA measurements for at least two reasons. First, both parties can be confident of an objective measurement of the weather phenomenon on which the contract will be settled. Second, buyers (sellers) can base bid (offer) prices on an extended time series of data collected at the site. 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 purpose of this study is to find optimal on-farm crop management strategies and index insurance strategies to reduce the risk associated with weather variability, and how these strategies vary spatially and temporally with different weather and soil conditions. Three weather stations and three soil types for Mitchell, Miller, and Lee Counties respectively are used to account for spatial variability. Based on the best crop management, index insurance products are designed to help farmers further reduce production risk. Optimal levels of index insurance parameters are solved to maximize expected utility for each index insurance product. The influence of basis risk is also examined.

Literature Review

A number of studies have used simulation models to evaluate crop production schedules based on plant growth relationships. 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 which 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 (IRDDESS), 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. Their results illustrate the potential role of decision support systems in the evaluation and management of large irrigation projects.

Apart from crop managemnt strategies, farmers also choose insurance products to improve their risk profile (Schnitkey, Sherrick, and Irwin). 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. 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:

$$U = \frac{NR^{1-r}}{1-r}, \qquad (1)$$

where NR is the return to the decision maker; r is the relative risk aversion coefficient. This model is employed in this paper to examine crop management strategies and precipitation contract design across different levels of risk aversion coefficients.

A crop simulation model, DSSAT model, is used to find optimal crop management stratigies. Irrigation and planting date are two input variables we want to optimaize. The optimal strategy is chosen from 21*4 combinations of strategies (irrigation threshold ranges from 5 to 99 in steps of 5 in addition to no irrgation; planting date include 4/20, 4/25, 5/1, and 5/6). Farm yield, irrigation water use, and net revenues, are then generated for various combinations of strategies, were generated by DSSAT (Decision Support System for Agro–technology Transfer). We were then able to identify the plant–available water threshold that maximized the expected utility function.

$$MAX(EU) = \sum_{1997}^{2006} h_t \frac{NR_t^{1-r}}{1-r}$$
$$= \sum_{1997}^{2006} h_t \frac{(q_t P - w_t C_{pumping})^{1-r}}{1-r} \qquad (2)$$

Where E denotes the expectation operator, NR denotes net return to an irrigated farm; $C_{pumping}$ denotes per unit irrigation cost; w denotes irrigation amount, which is an output form DSSAT model and is positively related with irrigation threshold; q_t denotes crop yield; P denotes crop price; r denotes relative risk aversion coefficient; h_t denotes probability function for each year.

Two probability functions across years are under consideration - one is uniform distribution; the other one puts more weights on drought years to account for the possibility of decrasing precipitaion in the near future. We arbitrarily set the probabilities of three driest years as 0.2 for each year, and the probability of the other years as (40/7)%. The analytical framework is also expanded to accommodate sensitivity analysis involving gradual change in the magnitude of risk aversion to determine changes in irrigation decisions. Comparison is also made from management perspective - one is dynamic crop management strategy that varies each year; one is static (constant) strategy over 10 years.

In the index insurance model, the critical components 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. If the index is positively correlated with crop yield, then a call option is appropriate; otherwise, a put option is appropriate.

In this study, we propose two unique index insurance products - one is weather derivative contract based on precipitation amount measured at the weather station; one is insurance product based on predicted yields from DSSAT. These contracts allow the purchasers to specify the parameters of the indemnity function according to their risk management needs. While the proposed contracts have characteristics much like a put option, we assume the highly tailored contracts and the relatively small dollar amount of protection required by most retail purchasers would necessitate sales through traditional retail insurance channels. 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, while the DSSAT yield contract trigger a payment when DSSAT simulated yield for a given year is less than a certain set strike DSSAT yield amount. The indemnity is paid conditional on the realization of the precipitation/DSSAT yield according to the following schedule:

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

where $f(i \mid x, i^*, \lambda)$ is the indemnity; i is the rainfall/DSSAT yield index for a specific period measured not at the farm as in (3) (in the crop simulation model) but rather at the weather station referenced in the insurance contract; i^* is the strike; $\lambda * i^*$ is the limit variable, and x is the maximum indemnity. The contract triggers an indemnity whenever i falls below i^*. In addition to allowing purchasers to tailor the characteristics of index options according to their risk management needs, the limit variable makes rating of precipitation puts more tractable. Specifically, 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. By their choices of strike and limit, purchasers define the domain of x over which the option will pay the indemnity.

The premium on the precipitation standard contract is a function of i^*, λ, x, and the probability distribution of i. The distribution is estimated based on historical precipitation data by using a nonparametric approach. Kernel smoothing is used to derive a continuous probability density function $h(i)$ of i. Formally, for index realizations i; t = 1,…,T, the kernel density function of the index is calculated as:

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

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:

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

The above formulation for calculating the pure premium is based on the pure indemnity 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 γ ($\gamma \geqslant 0$) is applied to the actuarially fair premium to cover transaction costs, return on investment, and reserve–building, then the loaded premium is:

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

For the purposes of this study, a 2% load is imposed on the standard deviations of indemnity payments per liability. The irrigation cost during the driest years is considered a good proxy for the value at risk and used to establish a liability estimate by crop. The remaining parameters for the contract are the strikes i* and limit parameter λ, which are selected to maximize the Expected Utility function over a historic period (1997–2006).

$$MAX(EU) = \sum_{1997}^{2006} h_t \frac{\left[(NR_{without})_t + f_t(i_t \mid x, i^*, \lambda) - \pi(x, i^*, \lambda)\right]^{1-r}}{1-r} \qquad (7)$$

Where $NR_{without}$ denotes net return to an irrigated farm without weather derivative contract; f_t denotes instrument payoff (indemnity) for year t; π is contract premium. Once the contract parameters strike, liability and limit are solved, fair premium and loaded premium rates can be formulated.

The impact of geographical basis risk was assessed by comparing the risk reduction generated from index insurance contracts based on different weather stations; the impact of temporal basis risk is assessed by allowing separate contracts to be purchased for different sub-periods during the entire period. A sub-period precipitation insurance, which partitions the growing season into 3 parts, and designs 3 different sets of insurance parameters for each period, is proposed and analyzed. The objective function of the sub-period contract is:

$$MAX(EU) = \sum_{1997}^{2006} h_t \frac{\left[(NR_{without})_t + f_t^1 - \pi^1 + f_t^2 - \pi^2 + f_t^3 - \pi^3\right]^{1-r}}{1-r} \qquad (8)$$

Where $f_t^1, \pi^1, f_t^2, \pi^2, f_t^3, \pi^3$ are indemnities and premiums for 3 subsequent sub-period contracts respectively.

Certainty–equivalent revenues (CER) were used to assess the robustness of the risk reduction performance of the optimal crop management 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. Using the utility function in equation (1), the certainty–equivalent revenues (CER) can be calculated as:

$$CER = ((1-r)(EU(NR))^{\frac{1}{1-r}} \quad (9)$$

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. Daily weather data for Mitchell, Miller, and Lee Counties are available from the United States National Climate Data Center (NCDC). Evapotranspiration rates are calculated from daily weather data using Priestley–Taylor Methods. 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

A cotton production example is used to illustrate the procedure described above. The results are organized as follows. The first section shows optimal on-farm crop management stratities that maximizes producer's expected utility, and how these strategies vary with the magnitude of risk aversion. The results from two probability distributions are compared. Static versus dynamic crop management methods are also compared and discussed.

Regional estimates for two index insurance, the precipitation insurance and the DSSAT yield insurance, are developed in second section for the study areas. The impact of the index insurance products on producers' Certainty Equivalent Revenue and the influence of geographic and temporal basis risk are also analyzed. A sub-period precipitation which is intended to reduce index contract's temporal basis risk is also analyzed and discussed.

Optimal Crop Management Strategies

Table 1 o 3 shows the optimal crop management strategies for cotton production in Mitchell County over different levels of risk aversion levels. CER can be considered as "compensated net revenue" that takes into account risk measures, and thus CER is always less than expected net return. For cotton production in Mitchell County, soil 1, over a large range of risk aversion levels (from r=1.5 to 5.5), optimal irrigation threshold is constant 40%, and optimal planting date is constant April 20. The only different strategy is for very high risk averse producers (r=6), with irrigation threshold being 45%, and planning date being April 25.

Table 1. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 1.

	R	Planting date	moisture	Expected_water	Expected_Yield	Expected_Net_Return	CER
1	1.5	20-Apr	40	2.71	4020.6	1560.2	1543.8
1	2	20-Apr	40	2.71	4020.6	1560.2	1538.2
1	2.5	20-Apr	40	2.71	4020.6	1560.2	1532.6
1	3	20-Apr	40	2.71	4020.6	1560.2	1526.9
1	3.5	20-Apr	40	2.71	4020.6	1560.2	1521.3
1	4	20-Apr	40	2.71	4020.6	1560.2	1515.7
1	4.5	20-Apr	40	2.71	4020.6	1560.2	1510.1
1	5	20-Apr	40	2.71	4020.6	1560.2	1504.6
1	5.5	20-Apr	40	2.71	4020.6	1560.2	1499.1
1	6	25-Apr	45	2.84	4004.8	1540.0	1494.3

For cotton production in Mitchell County Soil 2, optimal planting date is the same (April 20) across all risk averse levels, while irrigation threshold is 35% for low risk averse producers (r=1.5 to 2.5) and is 30% for higher risk averse producers (r=3 to 6).

Table 2. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 2.

soil	R	Planting date	moisture	Expected_water	Expected_Yield	Expected_Net_Return	CER
2	1.5	20-Apr	35	1.50	4091.9	1711.8	1697.1
2	2	20-Apr	35	1.50	4091.9	1711.8	1692.2
2	2.5	20-Apr	35	1.50	4091.9	1711.8	1687.2
2	3	20-Apr	30	1.32	4059.1	1708.8	1682.8
2	3.5	20-Apr	30	1.32	4059.1	1708.8	1678.5
2	4	20-Apr	30	1.32	4059.1	1708.8	1674.2
2	4.5	20-Apr	30	1.32	4059.1	1708.8	1669.9
2	5	20-Apr	30	1.32	4059.1	1708.8	1665.7
2	5.5	20-Apr	30	1.32	4059.1	1708.8	1661.6
2	6	20-Apr	30	1.32	4059.1	1708.8	1657.5

For cotton production in Mitchell County Soil 3, for producers with risk aversion level from 1.5 to 5, optimal planting date is April 20 and optimal irrigation threshold is 35%; for producers with risk aversion level from 5.5 to 6, optimal planting date is April 25 and optimal irrigation threshold is 30%.

Table 3. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 3.

soil	R	Planting date	moisture	Expected_ water	Expected_ Yield	Expected_Net_ Return	CER
3	1.5	20-Apr	35	1.62	4083.6	1695.9	1681.6
3	2	20-Apr	35	1.62	4083.6	1695.9	1676.8
3	2.5	20-Apr	35	1.62	4083.6	1695.9	1672.0
3	3	20-Apr	35	1.62	4083.6	1695.9	1667.3
3	3.5	20-Apr	35	1.62	4083.6	1695.9	1662.5
3	4	20-Apr	35	1.62	4083.6	1695.9	1657.7
3	4.5	20-Apr	35	1.62	4083.6	1695.9	1653.0
3	5	20-Apr	35	1.62	4083.6	1695.9	1648.4
3	5.5	25-Apr	30	1.40	4016.2	1676.2	1643.9
3	6	25-Apr	30	1.40	4016.2	1676.2	1641.0

Table 4 to 6 presents the results of optimal crop management for cotton production in Mitchell County when higher weight is put to drought years. Years 1999, 2000, and 2002 are the driest year with lowest rainfall amount during cotton growing season. An arbitrary probability of 20% is assigned to these years while probability of (40%/7) is assigned to the other 7 years, to indicate the current trends in decreasing rainfall.

The results show that for soil 1, comparing with the result for the uniform distribution, across different risk aversion levels, except for very high risk averse producers(r=6) who keep irrigation threshold as 45%, producers with lower risk averse levels increase irrigation threshold from 40% to 45%, and optimal planting date changes from April 20 to April 25, and the resulting irrigation water amount increases from 2.71mm/acre to 2.89mm/acre. For high risk averse producers (r=6), both irrigation and planting date strategy doesn't change. The change in expected water is due to higher weight is put on drier years with higher irrigation application.

Table 4. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 1 with Larger Weight on Dry Years.

soil	R	Planting date	moisture	Expected_water	Expected_Yield	Expected_Net_Return	CER
1	1.5	25-Apr	45	2.89	3972.6	1515.8	1508.9
1	2	25-Apr	45	2.89	3972.6	1515.8	1506.7
1	2.5	25-Apr	45	2.89	3972.6	1515.8	1504.4
1	3	25-Apr	45	2.89	3972.6	1515.8	1502.1
1	3.5	25-Apr	45	2.89	3972.6	1515.8	1499.9
1	4	25-Apr	45	2.89	3972.6	1515.8	1497.7
1	4.5	25-Apr	45	2.89	3972.6	1515.8	1495.4
1	5	25-Apr	45	2.89	3972.6	1515.8	1493.2
1	5.5	25-Apr	45	2.89	3972.6	1515.8	1491.0
1	6	25-Apr	45	2.89	3972.6	1515.8	1488.8

For soil 1, except for low risk averse producers (r=1.5 to 2.5) who keep irrigation threshold as 35%, other producers increase irrigation threshold from 30% to 35%. Across different levels of risk aversion, optimal planting date changes from April 20 to April 25, and the resulting irrigation water amount increases from 1.55mm/acre for low risk averse producers and 1.32 mm/acre for high risk averse producers to 1.60mm/acre. This result is same as our expectation: with higher weight put on drought years, optimal irrigation threshold incrasesa and the resulting expected water use increases.

Table 5. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 2 with Larger Weight on Dry Years.

soil	R	Planting date	moisture	Expected_water	Expected_Yield	Expected_Net_Return	CER
2	1.5	25-Apr	35	1.60	4013.7	1656.2	1650.9
2	2	25-Apr	35	1.60	4013.7	1656.2	1649.1
2	2.5	25-Apr	35	1.60	4013.7	1656.2	1647.4
2	3	25-Apr	35	1.60	4013.7	1656.2	1645.6
2	3.5	25-Apr	35	1.60	4013.7	1656.2	1643.9
2	4	25-Apr	35	1.60	4013.7	1656.2	1642.1
2	4.5	25-Apr	35	1.60	4013.7	1656.2	1640.4
2	5	25-Apr	35	1.60	4013.7	1656.2	1638.7
2	5.5	25-Apr	35	1.60	4013.7	1656.2	1637.0
2	6	25-Apr	35	1.60	4013.7	1656.2	1635.3

For Soil3, except for very high risk averse producers (r=5.5 to 6) who keep irrigation threshold level as 30% and keep planting date as April 25, other producers changes planting date from April 20 to April 25 and increase irrigation from 35% to 40%.

Table 6. Optimal Crop Management Strategies for cotton production in Mitchell County Soil 2 with Larger Weight on Dry Years.

soil	R	Planting date	moisture	Expected_water	Expected_Yield	Expected_Net_Return	CER
3	1.5	25-Apr	40	1.81	4036.4	1651.4	1645.6
3	2	25-Apr	40	1.81	4036.4	1651.4	1643.7
3	2.5	25-Apr	40	1.81	4036.4	1651.4	1641.8
3	3	25-Apr	40	1.81	4036.4	1651.4	1639.9
3	3.5	25-Apr	40	1.81	4036.4	1651.4	1638.0
3	4	25-Apr	40	1.81	4036.4	1651.4	1636.1
3	4.5	25-Apr	40	1.81	4036.4	1651.4	1634.3
3	5	25-Apr	40	1.81	4036.4	1651.4	1632.4
3	5.5	25-Apr	30	1.55	3995.6	1650.2	1630.7
3	6	25-Apr	30	1.55	3995.6	1650.2	1629.0

The previous results assumes when one strategy is chosen, it cannot be adjusted during the 10 years. Table 7 to 9 are the results of dynamic crop management for 3 soil types which assumes that crop management strategy can varies every year. The result shows that any one of the 4 planting dates can be chosen for a given year, and the same for irrigation strategies. Thus, there is no dominant static strategy that should be applied over the whole 10 years.

Table 7. Dynamic Crop Management Strategies for Cotton Production in Mitchell County Soil 1.

year	soil	Planting_date	moisture	yield
1997	1	April 25	40	4308
1998	1	April 20	55	4505
1999	1	May 1	60	4220
2006	1	April 20	45	4076
2001	1	April 20	45	4402
2002	1	May 6	55	3915
2003	1	April 20	40	4346
2004	1	April 20	45	4296
2005	1	May 6	45	3752
2006	1	April 20	40	3610

Table 8. Dynamic Crop Management Strategies for Cotton Production in Mitchell County Soil 2.

year	soil	Planting_date	moisture	yield
1997	2	April 20	35	4389
1998	2	April 20	50	4513
1999	2	May 1	45	4220
2006	2	April 20	40	4155
2001	2	April 20	40	4438
2002	2	May 6	50	3915
2003	2	April 20	5	4306
2004	2	April 20	40	4312
2005	2	May 6	35	3771
2006	2	April 20	30	3631

Table 9. Dynamic Crop Management Strategies for Cotton Production in Mitchell County Soil 3.

year	soil	Planting_date	moisture	yield
1997	3	April 20	40	4396
1998	3	April 20	50	4514
1999	3	May 1	40	4225
2006	3	April 20	40	4147
2001	3	April 20	40	4458
2002	3	April 25	40	3925
2003	3	April 20	5	4325
2004	3	April 20	40	4323
2005	3	May 6	35	3791
2006	3	April 20	55	3713

Table 10 to 12 illustrates the differences in Certainty Equivalent Revenue between static and dynamic strategies. It can be seen that for Soil 1 and Soil 2, CER increases by around 20$/acre over all levels of risk aversions. For Soil 3, CER increases by around 27$/acre. Therefore, a dynamic scheduling results in higher CER over 10 years than a static scheduling does. We calculate the differences between dynamic and static strategies under expected utility maximization, and conclude that a dynamic scheduling results in higher net revenue each year and higher expected utility over 10 years than a static scheduling does.

Table 10. Comparing of CER between Static and Dynamic Crop Management Strategies in Mitchell County Soil 1.

soil	R	CER_stat	CER_dynamic	CER_change
1	1.5	1543.8	1564.1	20.4
1	2	1538.2	1558.7	20.5
1	2.5	1532.6	1553.3	20.7
1	3	1526.9	1547.8	20.9
1	3.5	1521.3	1542.4	21.1
1	4	1515.7	1537.0	21.3
1	4.5	1510.1	1531.6	21.5
1	5	1504.6	1526.3	21.7
1	5.5	1499.1	1521.1	22.0
1	6	1494.3	1515.9	21.6

Table 11. Comparing of CER between Static and Dynamic Crop Management Strategies in Mitchell County Soil 2.

soil	R	CER_stat	CER_dynamic	CER_change
2	1.5	1697.1	1718.1	21.0
2	2	1692.2	1713.5	21.3
2	2.5	1687.2	1708.8	21.6
2	3	1682.8	1704.2	21.4
2	3.5	1678.5	1699.5	21.1
2	4	1674.2	1694.9	20.7
2	4.5	1669.9	1690.3	20.4
2	5	1665.7	1685.8	20.1
2	5.5	1661.6	1681.3	19.7
2	6	1657.5	1676.9	19.4

Table 12. Comparing of CER between Static and Dynamic Crop Management Strategies in Mitchell County Soil 3.

soil	R	CER_stat	CER_dynamic	CER_change
3	1.5	1681.6	1709.4	27.8
3	2	1676.8	1704.4	27.6
3	2.5	1672.0	1699.4	27.3
3	3	1667.3	1694.4	27.1
3	3.5	1662.5	1689.4	27.0
3	4	1657.7	1684.5	26.8
3	4.5	1653.0	1679.7	26.6
3	5	1648.4	1674.9	26.5
3	5.5	1643.9	1671.7	27.8
3	6	1641.0	1668.7	27.8

However, it should be noted that in reality, producers cannot exactly foresee weather condition before production, and thus it is not possible to choose best strategy each year. Thus, using maximizing expected utility based on past experience might be the best crop management available.

The next section analyzes whether index insurances can fill in the gap of the differences between dynamic and static strategies.

Regional Estimates for Precipitation Contracts

Table 13-15 presents optimal parameters for cumulative rain fall contract which is designed to provide protection over the total cotton growing season. For soil 1, best strike and lambda are 705 mm and 0.75 respectively for low risk averse producers and the corresponding premium rate is 0.579%. This contract doesn't improve purchasers' risk profile; instead, it decreases CER by 0.1-0.2. For higher risk averse producers, best strike and lambda are 1061.6mm and 0.95 respectively, both are large, which results in high probability of triggering indemnity and maximum liability, and thus the premium of the contract is high. The contract does improve high risk averse producers' CER, but not very much.

Table 13. Optimal Precipitation Contract for Cotton Production in Mitchell County Soil 1.

soil	r	Max_ Liability	expected_ rain	strike	lambda	tick	loaded_ premium	premium_rate	CER_ change
1	1.5	291.8	1061.6	705	0.75	1.7	1.7	0.579%	-0.1
1	2	291.8	1061.6	705	0.75	1.7	1.7	0.579%	-0.1
1	2.5	291.8	1061.6	705	0.75	1.7	1.7	0.579%	-0.1
1	3	291.8	1061.6	705	0.75	1.7	1.7	0.579%	-0.2
1	3.5	291.8	1061.6	705	0.75	1.7	1.7	0.579%	-0.2
1	4	291.8	1061.6	1255	0.95	4.7	228.3	78.227%	-0.1
1	4.5	291.8	1061.6	1255	0.95	4.7	228.3	78.227%	0.7
1	5	291.8	1061.6	1255	0.95	4.7	228.3	78.227%	1.5
1	5.5	291.8	1061.6	1255	0.95	4.7	228.3	78.227%	2.4
1	6	291.8	1061.6	1255	0.95	4.7	228.3	78.227%	3.3

For soil 2, 3 different contracts are designed for different producers with different levels of risk aversions. For low risk averse producers (r=1.5), best strike is 705, with premium rate being 0.759%. This contract doesn't improve their risk profile. For higher risk averse producers (r=2), best strike is 1095, with premium rate being 35.612%, and the contract still doesn't improve CER. For even higher risk averse producers (r=2.5 to 6), best contract is with strike 1115 and lambda 0.75, which can improve their CER, although the change in CER is not very large.

Table 14. Optimal Precipitation Contract for Cotton Production in Mitchell County Soil 2.

soil	r	Max_ Liability	expected_ rain	strike	lambda	tick	loaded_ premium	premium_rate	CER_ change
2	1.5	218.9	1061.6	705	0.75	1.2	1.3	0.579%	-0.1
2	2	218.9	1061.6	1095	0.75	0.8	77.9	35.612%	-0.1
2	2.5	218.9	1061.6	1105	0.75	0.8	81.5	37.228%	0.4
2	3	218.9	1061.6	1105	0.75	0.8	81.5	37.228%	0.9
2	3.5	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	1.5
2	4	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	2.2
2	4.5	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	2.8
2	5	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	3.6
2	5.5	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	4.3
2	6	218.9	1061.6	1115	0.75	0.8	84.8	38.733%	5.1

For soil 3, 6 different contracts are designed for different producers with different levels of risk aversions. While the contracts don't improve CER for low risk averse producers (r=1.5 to 3.5), they improve CER for high risk averse producers (r=4 to 6)

Table 15. Optimal Precipitation Contract for Cotton Production in Mitchell County Soil 3.

soil	r	Max_ Liability	expected_ rain	strike	lambda	tick	loaded_ premium	premium_rate	CER_ change
3	1.5	218.9	1061.6	675	0.75	1.3	1.0	0.457%	-1.0
3	2	218.9	1061.6	675	0.75	1.3	1.0	0.457%	-1.0
3	2.5	218.9	1061.6	675	0.75	1.3	1.0	0.457%	-1.0
3	3	218.9	1061.6	675	0.75	1.3	1.0	0.457%	-1.0
3	3.5	218.9	1061.6	1125	0.75	0.8	87.6	40.020%	-0.4
3	4	218.9	1061.6	1135	0.75	0.8	90.4	41.285%	0.9
3	4.5	218.9	1061.6	1145	0.75	0.8	93.1	42.528%	2.3
3	5	218.9	1061.6	1265	0.75	0.7	130.4	59.563%	3.7
3	5.5	218.9	1061.6	1265	0.75	0.7	130.4	59.563%	4.8
3	6	218.9	1061.6	1275	0.75	0.7	134.1	61.256%	5.8

Table 16 to 18 shows the results of optimal DSSAT yield index contract for cotton production in Mitchell County. For all three soil types, premium rates are around 41%, and they all improves producers' CER by amount larger than the precipitation contract does.

Table 16. Optimal DSSAT Yield Contract for Cotton Production in Mitchell County Soil1.

soil	r	Max_ Liability	expected_ yield	strike	lambda	tick	loaded_ premium	premium_ rate	CER_ change
1	1.5	291.8	4020.6	4191.0	0.9	0.7	117.8	40.376%	11.9
1	2	291.8	4020.6	4201.0	0.9	0.7	119.9	41.081%	16.7
1	2.5	291.8	4020.6	4201.0	0.9	0.7	119.9	41.081%	21.6
1	3	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	26.5
1	3.5	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	31.5
1	4	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	36.4
1	4.5	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	41.2
1	5	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	46.1
1	5.5	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	50.9
1	6	291.8	4020.6	4211.0	0.9	0.7	121.9	41.783%	55.6

Table 17. Optimal DSSAT Yield Contract for Cotton Production in Mitchell County Soil2.

soil	r	Max_ Liability	expected_ yield	strike	lambda	tick	loaded_ premium	premium_ rate	CER_ change
2	1.5	200.6	4091.9	4282.8	0.9	0.5	82.5	41.098%	9.1
2	2	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	12.7
2	2.5	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	16.4
2	3	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	19.5
2	3.5	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	22.5
2	4	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	25.5
2	4.5	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	28.5
2	5	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	31.4
2	5.5	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	34.2
2	6	200.6	4091.9	4292.8	0.9	0.5	83.4	41.564%	37.0

Table 18. Optimal DSSAT Yield Contract for Cotton Production in Mitchell County Soil3.

soil	r	Max_ Liability	expected_ yield	strike	lambda	tick	loaded_ premium	premium_ rate	CER_ change
3	1.5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	9.1
3	2	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	12.8
3	2.5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	16.5
3	3	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	20.2
3	3.5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	23.9
3	4	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	27.5
3	4.5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	31.1
3	5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	34.7
3	5.5	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	38.3
3	6	218.9	4083.6	4262.4	0.9	0.5	89.2	40.738%	41.7

However, high level of basis risk is present with DSSAT predicted yield index insurance because the predicted yields are not perfectly correlated with realized farm-level yield. In addition, since payments are based on the DSSAT county level predicted yield loss not the individual farmer's loss, individual crop losses may not be covered if the county yield does not suffer a similar level of loss. Thus the advantage of using DSSAT yield index insurance product could be dwarfed by high basis risk.

For weather derivative contract, basis risk also arises as precipitation amount measured at weather station is different from precipitation amount at farm level. For cotton producers in Mitchell County, the impact of geographical basis risk was assessed by comparing the risk reduction generated from index insurance contracts based on Miller and Lee weather stations.

Table 19-21 shows the comparisons of CER among CER without contract, CER with contract based on its weather station data, CER with contract based on weather data in Miller County, and CER with contract based on weather data in Lee County. We can see that for the contract based on weather data measured in Miller County, the benefit of contract no longer exist; the contract with basis risk now decreases producers' CER. For contract based on weather data measured in Lee county, comparing with CER without contract, the contract still have positive effect on CER, although the increase in CER is normally not as large as that for contract without basis risk.

Table 19. Comparison of CER among No contract, Contract with No Basis Risk, Contract Based on Weather in Miller County, and Contract Based on Weather in Lee County for Mitchell Soil 1.

soil	r	CER	CER_contract_nobasis	CER_contract_miller	CER_contract_lee
1	1.5	1543.8	1543.8	1543.5	1545.3
1	2	1538.2	1538.5	1537.9	1540.3
1	2.5	1532.6	1534.0	1532.2	1535.4
1	3	1526.9	1529.7	1526.5	1530.4
1	3.5	1521.3	1525.4	1520.8	1525.4
1	4	1515.7	1521.1	1515.1	1521.1
1	4.5	1510.1	1516.8	1509.4	1516.8
1	5	1504.6	1512.6	1503.9	1512.6
1	5.5	1499.1	1508.3	1498.3	1508.3
1	6	1494.3	1504.1	1492.9	1504.1

Table 20. Comparison of CER among No contract, Contract with No Basis Risk, Contract Based on Weather in Miller County, and Contract Based on Weather in Lee County for Mitchell Soil 2.

soil	r	CER	CER_contract_nobasis	CER_contract_miller	CER_contract_lee
2	1.5	1697.1	1698.7	1696.9	1697.7
2	2	1692.2	1694.6	1691.9	1693.0
2	2.5	1687.2	1690.4	1686.9	1688.4
2	3	1682.8	1686.1	1681.9	1684.0
2	3.5	1678.5	1681.7	1677.5	1679.6
2	4	1674.2	1677.2	1673.2	1675.2
2	4.5	1669.9	1672.6	1668.9	1670.7
2	5	1665.7	1667.9	1664.7	1666.3
2	5.5	1661.6	1663.2	1660.5	1662.2
2	6	1657.5	1658.4	1656.5	1658.2

Table 21. Comparison of CER among No contract, Contract with No Basis Risk, Contract Based on Weather in Miller County, and Contract Based on Weather in Lee County for Mitchell Soil 3.

soil	r	CER	CER_contract_ nobasis	CER_contract_ miller	CER_contract _lee
3	1.5	1681.6	1683.5	1681.4	1682.8
3	2	1676.8	1679.7	1676.6	1678.4
3	2.5	1672.0	1675.8	1671.7	1674.1
3	3	1667.3	1671.8	1666.9	1669.8
3	3.5	1662.5	1667.7	1662.0	1665.5
3	4	1657.7	1663.6	1657.2	1661.4
3	4.5	1653.0	1659.4	1652.5	1657.4
3	5	1648.4	1655.1	1647.8	1653.4
3	5.5	1643.8	1650.8	1643.2	1649.3
3	6	1641.0	1646.4	1638.6	1645.3

The impact of temporal basis risk is assessed by allowing separate contracts to be purchased for different subperiods during the entire period. The result shows that optimal contract parameters doesn’t vary across different levels of risk aversion, implying that an optimal contract can be designed for all kinds of cotton producers. Moreover, the results show that using separate insurance contracts for different time period will better improve producers' Certainty Equivalent Revenue.

Table 22. Optimal Sub-period Precipitation Contracts Parameters for Cotton Production in Mitchell County Soil 1

soil	r	Max_Liability	strike1	lambda1	strike2	lambda2	strike3	lambda3	tick1	tick2	tick3
1	1.5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	2	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	2.5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	3	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	3.5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	4	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	4.5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	5.5	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1
1	6	291.84	149.2	0.85	306.9	0.95	160.9	0.85	13.0	19.0	12.1

Table 23. Optimal Sub-period Precipitation Contracts Parameters for Cotton Production in Mitchell County Soil 2.

soil	r	Max_Liability	strike1	lambda1	strike2	lambda2	strike3	lambda3	tick1	tick2	tick3
2	1.5	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	2	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	2.5	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	3	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	3.5	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	4	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	4.5	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	5	218.88	149.2	0.85	306.9	0.95	160.9	0.85	9.8	14.3	9.1
2	5.5	218.88	149.2	0.95	306.9	0.95	160.9	0.85	29.3	14.3	9.1
2	6	218.88	149.2	0.95	306.9	0.95	160.9	0.85	29.3	14.3	9.1

Table 24. Optimal Sub-period Precipitation Contracts Parameters for Cotton Production in Mitchell County Soil 3.

soil	r	Max_Liability	strike1	lambda1	strike2	lambda2	strike3	lambda3	tick1	tick2	tick3
3	1.5	218.88	149.2	0.85	156.9	0.85	70.9	0.75	9.8	9.3	12.3
3	2	218.88	149.2	0.85	156.9	0.85	40.9	0.95	9.8	9.3	107.0
3	2.5	218.88	149.2	0.85	156.9	0.85	40.9	0.95	9.8	9.3	107.0
3	3	218.88	149.2	0.85	156.9	0.85	40.9	0.95	9.8	9.3	107.0
3	3.5	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0
3	4	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0
3	4.5	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0
3	5	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0
3	5.5	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0
3	6	218.88	149.2	0.85	156.9	0.75	40.9	0.95	9.8	5.6	107.0

Table 25. Premiums of Optimal Sub-period Precipitation Contracts and their Impact on CER for Cotton Production in Mitchell County Soil 1.

soil	r	loaded_premium1	premium_rate1	loaded_premium2	premium_rate2	loaded_premium3	premium_rate3	CER_sub_change
1	1.5	113.9	39.01%	204.7	70.15%	125.0	42.82%	1.06
1	2	113.9	39.01%	204.7	70.15%	125.0	42.82%	2.22
1	2.5	113.9	39.01%	204.7	70.15%	125.0	42.82%	3.40
1	3	113.9	39.01%	204.7	70.15%	125.0	42.82%	4.62
1	3.5	113.9	39.01%	204.7	70.15%	125.0	42.82%	5.86
1	4	113.9	39.01%	204.7	70.15%	125.0	42.82%	7.12
1	4.5	113.9	39.01%	204.7	70.15%	125.0	42.82%	8.41
1	5	113.9	39.01%	204.7	70.15%	125.0	42.82%	9.71
1	5.5	113.9	39.01%	204.7	70.15%	125.0	42.82%	11.03
1	6	113.9	39.01%	204.7	70.15%	125.0	42.82%	12.36

Table 26. Premiums of Optimal Sub-period Precipitation Contracts and their Impact on CER for Cotton Production in Mitchell County Soil 2.

soil	r	loaded_premium1	premium_rate1	loaded_premium2	premium_rate2	loaded_premium3	premium_rate3	CER_sub_change
2	1.5	85.4	39.01%	153.5	70.15%	93.7	42.82%	0.46
2	2	85.4	39.01%	153.5	70.15%	93.7	42.82%	1.25
2	2.5	85.4	39.01%	153.5	70.15%	93.7	42.82%	2.08
2	3	85.4	39.01%	153.5	70.15%	93.7	42.82%	2.95
2	3.5	85.4	39.01%	153.5	70.15%	93.7	42.82%	3.86
2	4	85.4	39.01%	153.5	70.15%	93.7	42.82%	4.81
2	4.5	85.4	39.01%	153.5	70.15%	93.7	42.82%	5.80
2	5	85.4	39.01%	153.5	70.15%	93.7	42.82%	6.82
2	5.5	102.1	46.67%	153.5	70.15%	93.7	42.82%	7.92
2	6	102.1	46.67%	153.5	70.15%	93.7	42.82%	9.09

Table 27. Premiums of Optimal Sub-period Precipitation Contracts and their Impact on CER for Cotton Production in Mitchell County Soil 3.

soil	r	loaded_premium1	premium_rate1	loaded_premium2	premium_rate2	loaded_premium3	premium_rate3	CER_sub_change
3	1.5	85.4	39.01%	5.6	2.56%	12.4	5.67%	(3.69)
3	2	85.4	39.01%	5.6	2.56%	1.0	0.46%	(2.32)
3	2.5	85.4	39.01%	5.6	2.56%	1.0	0.46%	(0.78)
3	3	85.4	39.01%	5.6	2.56%	1.0	0.46%	0.81
3	3.5	85.4	39.01%	1.0	0.46%	1.0	0.46%	2.49
3	4	85.4	39.01%	1.0	0.46%	1.0	0.46%	4.35
3	4.5	85.4	39.01%	1.0	0.46%	1.0	0.46%	6.26
3	5	85.4	39.01%	1.0	0.46%	1.0	0.46%	8.23
3	5.5	85.4	39.01%	1.0	0.46%	1.0	0.46%	9.69
3	6	85.4	39.01%	1.0	0.46%	1.0	0.46%	11.11

Conclusions

Crop simulation models offer new opportunities to explore crop management strategies and financial instruments to reduce crop production risk. We used the DSSAT model to simulate yield, revenue, and irrigation cost responses to various irrigation and planting date strategies over 10 years. Optimal crop management strategies for cotton production in Mitchell, Miller, and Lee counties varies largely across different counties, but appear to be largely independent of risk–aversion levels.

Based on the best crop management, index insurance products are designed to help farmers further reduce production risk. This study examines the feasibility of two index insurance products - one is weather derivative contract based on precipitation amount measured at the weather station; one is insurance product based on predicted yields from DSSAT. The result shows that Certainty Equivalent Revenue can be improved by these index insurance products, especially by DSSAT yield index insurance.

The impact of geographical basis risk was assessed by comparing the risk reduction generated from index insurance contracts based on different weather stations. The results show that the advantage of using index insurance products is reduced by high basis risk; however, even in the presence of basis risk, contract for cotton production in Mitchell County based on weather data in Lee County is still attractive compared with no-contract.

The impact of temporal basis risk is assessed by allowing separate contracts to be purchased for different subperiods during the entire period. The result shows that Using separate insurance contracts for different time period will further improve CER for cotton producers in Mitchell County.

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