Journal of Agricultural and Applied Economics, 43,4(November 2011):529–540

Mitigating Cotton Revenue Risk Through Irrigation, Insurance, and Hedging

E. Hart Bise Barham, John R.C. Robinson, James W. Richardson, and M. Edward Rister

This study focuses on managing cotton production and marketing risks using combinations of irrigation levels, put options (as price insurance), and crop insurance. Stochastic cotton yields and prices are used to simulate a whole-farm financial statement for a 1,000 acre furrow-irrigated cotton farm in the Texas Lower Rio Grande Valley under 16 combinations of risk management strategies. Analyses for risk-averse decision makers indicate that multiple irrigations are preferred. The benefits to purchasing put options increase with yields, as they are more beneficial when higher yields are expected from applying more irrigation applications. Crop insurance is strongly preferred at lower irrigation levels.

Key Words: cotton, crop insurance, irrigation, options, puts, risk, simulation, stochastic efficiency with respect to a function

JEL Classifications: D81, Q12, Q15

Cotton is the top cash crop for Texas, with a statewide economic impact of $4 billion (Hudgins, 2003; Robinson and McCorkle, 2006). Despite the large economic impact, cotton farming in Texas is subject to considerable risk. For example, a 2002 drought in Texas caused statewide cotton losses of $95 million in farm gate value (Hudgins, 2003). In general, the dry Texas climate implies that water availability, through either irrigation or rainfall, is a major source of production risk.

For some irrigated Texas regions, even the supply of irrigation water can be risky. For example, the Texas Lower Rio Grande Valley (hereafter, LRGV) crop production is dependent on variable water supplies in reservoirs along the Rio Grande River (Stubbs et al., 2003). With sufficient irrigation, LRGV cotton can yield up to 1,500 lbs/acre and the yield is more stable than non-irrigated cotton. As a result, irrigated cotton usually receives more cost effective crop insurance coverage than dryland cotton (Zuniga, Coble, and Heifner, 2001).

Cotton producers also face variable prices from uncertainty of aggregate supplies, uncertain foreign demand, and government trade policies. There are several alternatives available to producers for managing price variability risks, including farm programs, marketing or cooperative pools, forward contracting, and hedging (Robinson et al., 2006). The specific location of a farming operation can also influence price variability. A natural hedge occurs in areas that produce large enough cotton supplies to affect the national price, creating a negative correlation between price and yield. For example, the Texas Southern High Plains (an extensive cotton growing region) would have a much stronger

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price/yield correlation than a smaller production region like the LRGV.[1] Areas like the LRGV with a weaker natural hedge may find forward contracting or hedging useful for reducing price risk, however (Harwood et al., 1999).

This paper examines the risk efficiency of alternative combinations of risk management tools over a range of risk aversion levels for a representative LRGV cotton farming operation. The research extends the literature on farm risk management by considering the risk mitigating aspects of irrigation in combination with crop insurance, hedging, and farm programs. Previous research has demonstrated that crop insurance and irrigation are partial substitutes, while forward pricing has been shown to complement crop yield insurance (Coble et al., 2002; Coble, Heifner, and Zuniga, 2000; Dalton, 2004). Zuniga, Coble, and Heifner (2001) is an example of further combining yield insurance, hedging, and government programs. The research considered in the present paper adds various levels of irrigation to hedging and insurance decisions, within the existing farm program framework.

Irrigation strategies are commonly viewed as yield enhancing, but they are also mitigating the risk of lower yield outcomes (Lin, Mullen, and Hoogenboom, 2008; Senft, 1992). Timing of irrigation applications and the amount of water administered have been two common research topics. For example, Pandey (1990) found that higher levels of water application were risk efficient at low levels of risk aversion, but that the preference for water applications declined at higher risk aversion levels. Dalton (2004) examined the interaction of crop insurance and irrigation as risk management strategies using an expected utility framework. The study used an *ex ante* bioeconomic simulation approach and derived certainty equivalents for each decision alternative. Dalton concluded that irrigation strategies provide risk management benefits as risk aversion increases, and federal crop insurance programs were inefficient in reducing exposure to production risk from variable rainfall. The more recent paper by Lin, Mullen, and Hoogenboom (2008) used biophysical simulation to evaluate both risk efficient irrigation levels and the effectiveness of weather derivatives as a risk mitigation tool.

To summarize the literature cited above, the combination of forward pricing and crop insurance appears to be a complementary risk management strategy, and irrigation appears to be a general substitute for crop insurance, although this has not been studied for varying levels of irrigation. No studies were found that examine the triple interaction of insurance, forward pricing, and irrigation level as risk management strategies.

Sixteen combinations of irrigation levels, put options, and crop insurance are examined in this research. A Monte Carlo simulation model is developed to simulate probability distributions of net returns for a representative LRGV cotton farm. Many models have used simulation to generate distributions for key output variables such as net returns, e.g., Bailey and Richardson (1985); Coble, Zuniga, and Heifner (2003); Harris and Mapp (1986); Lien, Hardaker, and Flaten (2007), Lien et al. (2007); Pandey (1990); Ribera, Hons, and Richardson (2004); and Zuniga, Coble, and Heifner (2001). The probability distributions of net returns are typically ranked using various procedures. This paper ranks probability distributions initially with stochastic dominance and then with stochastic efficiency with respect to a function (hereafter, SERF) (Hardaker 2004a, 2004b).

Methods

Model

A single-period Monte Carlo financial model of a 1,000 acre furrow-irrigated cotton farm in

[1] In response to an anonymous reviewer, we estimated correlation coefficients of -0.48 and -0.51 between LRGV yields and, respectively, cash price or December futures, over the study period of 1976–2005. Neither yield-price correlation was significantly different from zero at the 95% level, but both correlations were significant at the 90% level. So there appears to be only a weak correlation. When we further omitted the spurious association of very low 1995 LRGV yields and correspondingly high prices (the latter attributed to U.S. and international conditions), the resulting yield-price correlations were in the range of -0.20 for both futures and cash prices, neither of which were significantly different from zero at the 90% level. Our conclusion is that our original assumption of negligible yield-price is correct, and that our option hedge methodology is unaffected.

the LRGV was built. Risk management control variables in the model included (a) zero, one, two, or three irrigation applications; (b) purchase (or not) of a 65% multiple peril crop insurance policy; and (c) purchase (or not) of put options on total expected production. Combinations of these three basic strategies comprised 16 different scenarios (i.e., 4 × 2 × 2 choices, respectively). The key output variable for the model was whole farm net return, which was simulated for each of the 16 risk management strategies. The probability distribution of whole farm net returns for the 16 alternatives can be used by a hypothetical decision maker (DM) to rank the expected benefits of alternative risk management strategies. The stochastic variables were yield, cash price, and futures price, with random draws made from all three of these variables. Whole farm net return was calculated using the formula:

$$\text{Net Return} = \text{Total Revenue} - \text{Total Specified Cost} \tag{1}$$

where:

$$\text{Total Specified Cost} = (\text{Irrigation Cost} + \text{Option Premium} + \text{Insurance Premium} + \text{Other Production Costs}^{2}) * \text{Acres}; \tag{2}$$

$$\text{Total Revenue} = \text{Price} * \text{Yield} * \text{Acres} + \text{Insurance Indemnity Payments} + \text{Government Payments}; \tag{3}$$

$$\text{Price} = \text{Mean Price} * [1 + \text{MVE}\ (S_i\ F(S_i), \text{CUSD}_1)]; \text{ and} \tag{4}$$

$$\text{Yield} = \text{Mean Yield} * [1 + \text{MVE}\ (S_i\ F(S_i), \text{CUSD}_2)]. \tag{5}$$

$CUSD_1$ and $CUSD_2$ are correlated uniform standard deviates which were simulated using the correlation matrix for cotton yield and price from 1976–2005 as described by Richardson, Klose, and Gray (2000). MVE is a multivariate empirical distribution. Mean Price in Equation (4) is the mean of the national season average cotton price from 1976–2005.

Mean Yield in Equation (5) is the expected cotton yield per acre. The latter was based on regional Extension budgets for non-irrigated (500 lbs lint per acre) and irrigated cotton (825 lbs lint per acre) where the irrigated cotton budget reflects two furrow irrigation applications of 4.75 acre-inches each (Texas AgriLife Extension Service – Texas A&M University System, 2006). The budget mean irrigated yields were scaled to match the specific treatment applications examined in this study, i.e., one, two, and three furrow irrigation applications of 6 acre-inches each. The scaling involved an irrigated cotton production function developed for the LRGV study area (Harman et al., 2005). Deterministic predictions of yield from this production function were estimated using 6, 9.5, 12, and 18 acre-inches of total irrigation water, combined with an average annual 24 inches of precipitation. These yield estimates were then scaled proportionately lower to reflect the Extension budget relationship of 9.5 inches of irrigation and an 825 lb yield. The rationale for the scaling was the level of yield in the Extension budgets account for average pest losses whereas Harman et al.'s production function does not. The resulting expected yield values per acre (by irrigation level) were 500 lbs (zero irrigation), 634 lbs (one irrigation), 947 lbs (two irrigations), and 1,189 lbs (three irrigations). The variability around these expected yields was characterized by using biophysical simulation (discussed in the following section).

In Equations (4) and (5), sorted deviations from the mean are denoted by S_i, and $F(S_i)$ is the cumulative probability for S_is. The MVE distribution for yields and prices was used and the stochastic variables were expressed as fractional deviations from the means for calculating the parameters to simulate the stochastic variables. This method forces constant relative risk for any assumed mean (Richardson, Klose, and Gray, 2000). The procedures for estimating parameters and simulating MVE probability distributions are described by Richardson (2006).

[2] Other production costs included specified variable and fixed costs by the Texas AgriLife Extension Service. Harvest related costs were calculated as [(Per Unit Harvest/Haul Rate + (Ginning Costs – Seed Value)] * Stochastic Yield}. Fixed costs did not include a land charge, so net returns in Equation (1) represent returns to land, management, and non-specified risk.

Characterization of Yield Risk

Field experimentation is costly, time consuming, and could adversely impact the economic viability of a farmer. As a consequence, there are generally inadequate data to develop probability distribution functions for cotton yields under alternative irrigation strategies. Such would be the case in our present study if we had tried to use observed yield data over multiple years and irrigation levels. On the other hand, simulated data from plant growth models can be molded to a researcher's specifications and are more easily accessible. Generating biophysical data with simulation is increasing in importance as a valid alternative to field experimentation (Musunuru et al., 2005). Previous studies have been based on simulated yield data from biophysical models that are validated against actual observed yields (Dalton, 2004; Harris and Mapp, 1986; Musunuru et al., 2005; Pandey, 1990).

A 50-year series of cotton yield data was simulated using the Crop Production Management (CroPMan) model (Blacklands Research and Extension Center – Texas A&M University System, 2006). This data series was used to estimate the probability distribution of cotton yields under alternative irrigation assumptions. The CroPMan model predicts a deterministic yield outcome for a given (and huge) set of plant growth parameters, local soil parameters, historical weather data, and other controlling variables.[3] To generate a yield distribution required applying CroPMan for a given set of site specific biophysical parameters over a successive number of historical weather conditions for that site. For the present study, cotton yields were simulated using 50 years of historical weather data for McAllen, Texas between 1956–2005 (Blacklands Research and Extension Center – Texas A&M University System, 2006). Other assumptions included Willacy fine sandy loam soil parameters (with 61% sand content), 600 ppm salt in the irrigation water, and current cotton variety growth parameters. As mentioned previously, the irrigation levels were zero, one, two, and three furrow applications of 6 inches of water per acre. The resulting CroPMan yield distributions were used to incorporate variability around the expected budget yields for the various levels of irrigation. Stochastic yields were simulated using a trend corrected empirical probability distribution as this distribution performed better than 15 parametric distributions using Simetar's distribution goodness of fit test (Richardson, 2006).

Price Data

Annual price observations from 1976 through 2005 were used to estimate the probability distribution for cotton cash and futures prices.[4] United States season average cash price data were obtained from the National Agricultural Statistics Service – United States Department of Agriculture (USDA) (2006). The local price of cotton was simulated using the stochastic national price plus a stochastic price wedge between the national price and local price. The average price wedge was estimated from a linear regression of harvest period national price and December futures prices between 1976 and 2005. The residuals for the regression were assumed

[3] CroPMan is a production-risk management aid that incorporates weather, soil type, pesticides/fertilizers, water application, and management decisions (Blacklands Research and Extension Center – Texas A&M University System, 2006). CroPMan employs the environmental policy impact calculator crop growth model with extensive databases of soil series data, historical weather data, machinery parameters, environmental parameters, hundreds plant growth coefficients, and other controlling variables (Williams, Jones, and Dyke, 1984). Using region-specific soil and weather databases, CroPMan has been validated in regional field validation trials for Texas cotton, and specifically for the LRGV (Supercinski, 2005). See Ko et al. (2009) for an example of a South Texas cotton field validation trial and the complexity of biophysical variables involved.

[4] The price series used in this analysis included annual observations of cotton cash and futures prices between 1976 and 2005, inclusive. We also conducted the risk analysis using a more recent subset of price data (1991 through 2005) but this did not affect the previous summary statistics comparisons or the SERF rankings. The price series ends in 2005 to match the period of water shortages in the study area, and also to account for evidence of a structural break in the relationship of various fundamental factors and cotton prices for the period 2006 through 2009 (Power and Robinson, 2010).

to be distributed normally for simulating the stochastic price wedge.

Harvest-time futures price consisted of a weighted[5] average of December cotton futures settlement prices centered around the first trading day in September for 1976–2005. The futures price data were compiled at Texas A&M University (Gleaton, 2006) from daily futures exchange settlements. The December futures contract was selected because it is the most heavily traded cotton contract, and the early September period is when LRGV cotton farmers complete harvest and presumably offset pre-harvest hedges.

Estimation and Evaluation of Probability Distributions

The stochastic variables were simulated using the MVE method described by Richardson, Klose, and Gray (2000). Ordinary least squares analysis indicated no statistically significant trend (at the 0.05 level) in yields or futures price, but there was a significant trend in cash price. Correlation was found in the historical data of several of the stochastic variables and a Student's *t*-test indicated statistical significance. Therefore, an MVE distribution was used to avoid biasing the results and to adequately represent the data from a small sample (Richardson, 2006; Richardson, Klose, and Gray, 2000).

Historical price and yield data were expressed as percent deviations from expected values. As mentioned above, expected yields were based on Extension budget yields (Texas AgriLife Extension Service – Texas A&M University System, 2006). The expected national cash price value was the forecasted 2007 farm price obtained from the Food and Agricultural Policy Research Institute – University of Missouri and Iowa State University (2007). The mean futures price used was forecasted by the Texas AgriLife Extension Service cotton marketing specialist (Robinson, 2006). Validation tests were performed to test if the simulated random variables statistically reproduced their respective historical distributions, as well as reproduced the historical correlation matrix.[6]

Financial Model

The stochastic yield and price variables were used in the whole-farm model to simulate net return for a 1,000 acre irrigated cotton farm in the LRGV. The same Extension representative cotton budgets previously used to specify expected yield were used to calculate production costs (Texas AgriLife Extension Service – Texas A&M University System, 2006). Variable and fixed costs were calculated individually for each irrigation level, as some costs vary according to yield and water applications. The costs that varied with yield were scaled by the mean or stochastic yield (depending on whether the price is determined before or after yields are known) for each level of irrigation.

For crop insurance, multiple peril crop insurance with 65% coverage and 100% price election was used, as this was the most representative level of insurance in the study area. The insurance yield (i.e., actual production history yield) was assumed to equal the expected yield at each irrigation level.[7] Crop insurance premiums were obtained from an on-line USDA calculator for the study area (Risk Management Agency – USDA, 2006).

[5] In each year, 29 observations centered around the first trading day in September were used to estimate a weighted average price based on the normal distribution of the number of trading days on either side of the first trading day in September. The mean of this distribution was zero and the standard deviation was 8.51 days. The probability mass function values were used to calculate weights, which valued the days closer to the first trading day in September more than those further away.

[6] The Hotelling's T^2 test was used to test that the simulated means were statistically equal to their assumed values. Box's *M* Squared test was used to test that the covariance for the simulated variables equaled the historical covariance matrix. Student's *t*-tests were used to test that the individual correlation coefficients among the simulated variables were statistically equal to their historical values.

[7] This approach assumes no conflicts with the Risk Management Agency and crop insurance adjustors regarding deficit irrigation within an irrigated practice policy. Full irrigation for cotton is represented by three irrigations. Based on discussions with local crop insurance representatives, this assumption may be valid for two or even one irrigation in years where there is a recognized shortage of irrigation water.

To operationalize the put option hedging strategy, a put option strike price of $0.60/lb was assumed as a representative hedging price target. The premium for this put option was based on the average of $0.60 strike put option settlements between December 15, 2006 and January 15, 2007 (i.e., reflecting a pre-season decision for a one-period model of the upcoming 2007 crop). Option contracts cover 50,000 pounds of production, so multiple put options were purchased to approximate (without exceeding) expected whole farm production for each irrigation strategy.

Operating loan interest included in the model was the only interest cost, as the model simulates farm costs for only 1 year. Operating loan interest was calculated based on the number of months the funds for each variable cost were borrowed. Variable cost was multiplied by the percentage of the year that it was used.

Counter-cyclical payments (CCP) and direct payments (DP) were included in the calculation of net return for all 16 scenarios. As these two payments are independent of actual production, their payment yields did not vary across scenarios. Assuming 2002 farm program provisions,[8] CCP and DP yields of 500 lbs/acre were used for dryland, and 625 lbs/acre were used for irrigated land (Agricultural and Food Policy Center, 2006). These yields reflected historical irrigated yields and are invariant to actual levels of irrigation or yield. The cotton loan rate, target price, direct payment rate, and payment fraction were obtained from the USDA Farm Service Agency (Farm Service Agency – United States Department of Agriculture, 2006). The DP payment rate was fixed, and the CCP rate was stochastic and based on the national cotton price.

Ranking Risky Scenarios

The 16 net return probability distributions (one for each risk management combination) were ranked using SERF. SERF calculates certainty equivalents (CE) over a range of risk aversion coefficients (RACs), rather than selecting a single RAC, and ranks risky alternatives based on the CE values over the range of RACs. The most preferred risky alternative is the one with the highest CE at each RAC. Anderson and Dillon (1992) defined degrees of relative risk aversion coefficients (RRAC), using zero to represent risk neutral decision makers and 4.0 to represent extremely risk-averse decision makers. A power utility function was used for the risk ranking.

Results and Discussion

Budget Comparisons

The mean yield per acre, irrigation input and costs per acre, other variable costs per acre (sans insurance and put option costs), fixed costs per acre, and net returns per acre are summarized in Table 1 across levels of irrigation. Non-irrigation variable costs tend to increase with increasing irrigation because many chemical inputs, not to mention harvest costs, are a function of yield. A comparison of these budget parameters across levels of irrigation explains some of the underlying differences in average net returns (e.g., the relative cost savings of zero irrigations outweighs the yield gain of one irrigation, so the average net returns to dryland exceeds that of one irrigation). However, the two and three irrigation budgets have enough yield response to give higher net returns than dryland (at the lint and water prices evaluated in this study).

Summary Statistics

The mean, standard deviation, coefficient of variation (CV), and minimum and maximum net returns from the simulated output for the 16 combinations of risky alternatives are presented in Table 2 for implementing put options and/or insurance at each irrigation level. A review of the summary statistics is useful in examining how particular risk management strategies affect net returns in the present model.

Table 2 results for "Irrigation Only" indicate that applying multiple irrigations increases whole

[8] 2002 farm program payment rates were used to be consistent with the 2007 setting of this model. For a post-2007 time frame, the farm program payment rates would need a small downward adjustment to reflect those authorized by the Food, Conservation, and Energy Act of 2008 commodity title, assuming no Average Crop Revenue Election.

Table 1. Selected Budget Parameters for a 1,000 Representative Cotton Farm in the Lower Rio Grande Valley, 2007

	Dryland	1 Irrigation	2 Irrigations	3 Irrigations
Yield (lbs/acre)	500	634	947	1,189
Total Irrigation Water (acre-inches)	0	6	12	18
Total Irrigation Cost/Acre (water and labor)	$0.00	$20.31	$40.62	$60.93
Other Non-Risk Management Variable Cost/Acre	$197.02	$260.51	$345.13	$396.75
Total Irrigation Plus Non-Risk Management Variable Cost/Acre	$197.02	$280.82	$385.75	$457.68
Total Fixed Cost/Acre	$71.31	$73.54	$73.54	$73.54
Net Returns/Acre at Loan Rate	−$8.33	−$24.68	$33.15	$87.06

farm mean net returns from $73,640 (zero irrigations) and $61,741 (one irrigation) to $154,405 (two irrigations) and $214,396 (three irrigations), and greatly reduces the variability of net returns. The variability reduction is evident by (1) the smaller standard deviation of $91,781 and $87,892 at two and three irrigations, respectively, compared with $238,559 and $237,092 at lower irrigation levels; and (2) the associated lower coefficients of variation with 59% and 41% for two and three irrigations, respectively, and 324% and 384% on zero and one irrigation, respectively. Also, the range from minimum net return to maximum net return is

Table 2. Simulated Net Return Summary Statistics for Various Levels of Irrigation for a 1,000 Acre Cotton Farm in the Lower Rio Grande Valley in 2007

	Zero	1 Irrigation	2 Irrigations	3 Irrigations
Irrigation Only				
Mean ($)	73,640	61,741	154,405	214,396
Standard Deviation ($)	238,559	237,092	91,781	87,892
Coefficient of Variation (%)	324	384	59	41
Minimum ($)	−203,074	−239,925	−130,083	−177,774
Maximum ($)	878,141	813,502	432,000	456,949
Irrigation and Put Options				
Mean ($)	94,988	87,359	192,831	263,496
Standard Deviation ($)	258,842	260,014	145,610	158,215
Coefficient of Variation (%)	273	298	76	60
Minimum ($)	−222,050	−262,696	−119,484	−164,231
Maximum ($)	998,647	958,109	648,911	734,113
Irrigation and Crop Insurance				
Mean ($)	137,578	121,052	164,052	211,170
Standard Deviation ($)	189,339	182,234	77,202	85,239
Coefficient of Variation (%)	144	151	47	40
Minimum ($)	−55,389	−87,883	−141,926	−183,202
Maximum ($)	865,202	800,891	420,157	445,699
Irrigation, Put Options and Crop Insurance				
Mean ($)	152,926	146,670	202,478	260,270
Standard Deviation ($)	210,572	206,937	134,722	157,349
Coefficient of Variation (%)	138	141	66	60
Minimum ($)	−69,314	−85,226	−131,327	−169,659
Maximum ($)	985,707	945,498	637,067	722,862

much smaller for multiple irrigations than for one irrigation and zero.

The risk aspects of increasing irrigation remain constant for all of the risk management strategies examined. For example, adding put options simply increases the mean, standard deviation, and range of net returns for all four irrigation levels. Mean net returns were increased from \$73,640, \$61,741, \$154,405, and \$214,396 (i.e., "Irrigation Only" in Table 2) to \$94,988, \$87,359, \$192,831, and \$263,496 (i.e., "Irrigation and Put Options" in Table 2) at zero, one, two, and three irrigation levels, respectively.

Combining put options with irrigation appears to increase variability of net returns, but the results depend on the level of irrigation. In absolute terms, the increased variability of net returns is reflected by larger standard deviations of net returns across all irrigation/put option combinations, relative to irrigation alone (Table 2). However, put option strategies resulted in higher mean net returns, with mixed results for variability relative to the mean, i.e., higher (lower) CVs for higher (lower) levels of irrigation. Put options involve paying the up-front option premiums, a pricing insurance strategy which sometimes pays off and sometimes does not. The outcome of this strategy matters more at higher levels of irrigation because it involves correspondingly higher levels of potential yield, potential gross income, and put option coverage.

Crop insurance and irrigation generate the smallest CV for two and three irrigations (47% and 40%, respectively) out of all 16 scenarios, and also the smallest standard deviations of net returns (Table 2). The ability of crop insurance to reduce the variability of net returns demonstrates the effectiveness of insurance to reduce the riskiness of net returns. It also confirms the observation that crop insurance for Texas cotton tends to pay off regularly (Stokes and Ortega, 2006).

Combining put options with two or three irrigations results in relatively higher mean net returns, albeit with added risk in relative terms, compared with combining crop insurance and higher levels of irrigation (Table 2). Crop insurance and irrigation result in lower risk and lower mean net returns relative to put options and higher irrigation levels. Following a discussion of stochastic dominance, the SERF procedure is utilized to rank the risky outcomes.

Risk Ranking

Inspection of the cumulative distribution functions (not shown) for all 16 scenarios had few consistent risk implications. In general, the combinations involving zero or one irrigation tended to have lower returns, except that 10% to 30% of the time these strategies dominated the higher irrigation strategies. This reflects those infrequent situations when adequate rainfall gives the lower irrigation strategies a cost advantage.

Due to extensive multiple crossing of the cumulative distributions for the 16 scenarios, only three scenarios were first degree stochastic dominant (FDSD); one irrigation is dominated in FDSD by: dryland with a put, by dryland with a put and insurance, and by one irrigation with a put and insurance. As a result, all 16 scenarios were ranked using SERF (Figure 1). The vertical axis in Figure 1 is certainty equivalents and the lines represent the CEs for each scenario calculated at the respective RRAC. A rational DM prefers a higher CE to a lower value at their particular RRAC, so the scenarios can be ranked by observing the highest CE at each relative risk aversion coefficient.

The most preferred risky alternative across ranges of relative risk aversion from 0–4 is three irrigations and put options. The CE line for this scenario is higher than all others for all classes of risk-averse decision makers with relative risk aversion between 0 and 4. The second most preferred alternative is three irrigations, put options, and crop insurance. The third most preferred alternative is three irrigations without insurance or a put option. Figure 1 also indicates that three irrigations are preferred for all combinations of risk management alternatives over only two irrigations. Put options are also preferred at two and three irrigation levels, both when insurance is used and when it is not. Two irrigations alone is preferred to one irrigation with puts and insurance for all risk-averse DMs.

Growing dryland cotton without insurance and puts is preferred to the least preferred scenario,

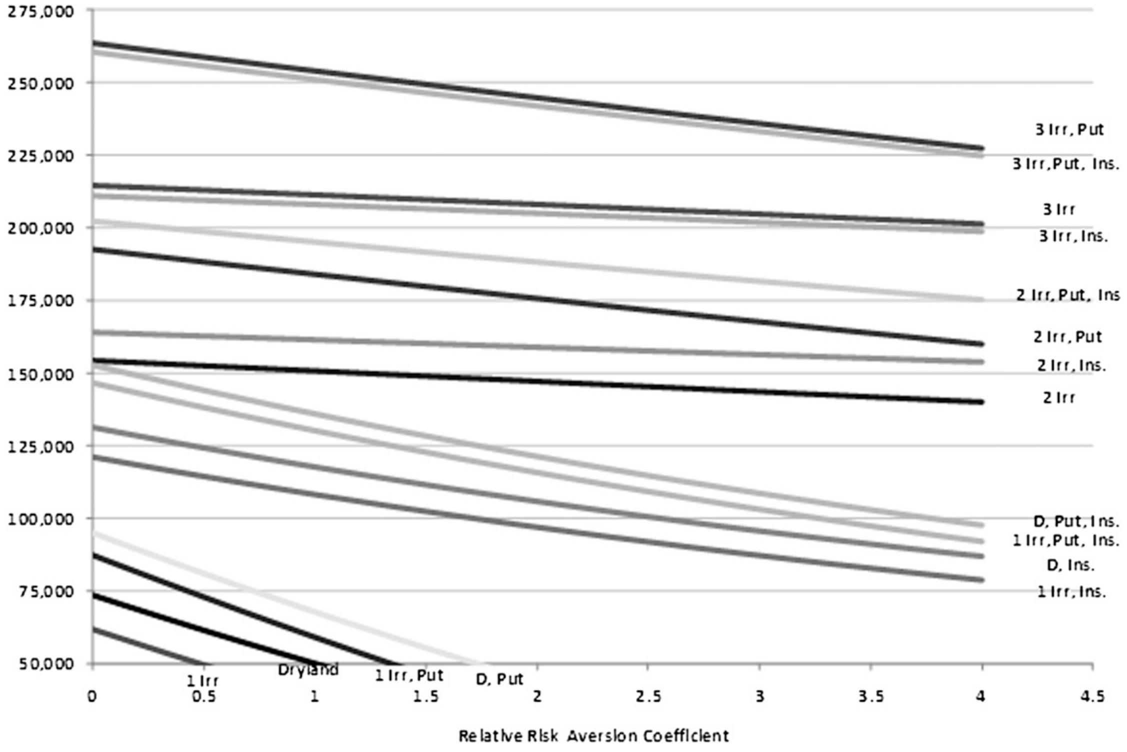

Figure 1. SERF Ranking of Risky Alternatives Over a Range of Relative Risk Aversion Coefficients Using a Power Utility Function for a 1,000 Acre Cotton Farm in the Texas Lower Rio Grande Valley[9] (Y-axis refers to certainty equivalents)

one irrigation with no insurance and no puts (Figure 1). Adding a put to the dryland or the one irrigation scenario increases its preference over the one irrigation and the dryland options.

Conclusions

In summary, all risk-averse decision makers (DMs), from risk neutral to extremely risk-averse, prefer put options at higher levels of irrigation and prefer crop insurance at lower levels of irrigation. These results agree with previous studies that crop insurance substitutes for higher levels of irrigation (Dalton, 2004).

The strength of the study lies in the examination of three basic risk management strategies analyzed under various combinations of scenarios, an approach that had not been utilized in previous studies. Extending the study to ranking of these risky alternatives across risk aversion levels using stochastic efficiency with respect to a function (SERF) took the study one step further. Ranking the scenarios showed three irrigations to have a significant positive impact on net returns, and that three irrigations

[9] 3 Irr, Put: three irrigations, with put options, no insurance
3 Irr, Put, Ins.: three irrigations, with put options, with insurance
3 Irr: three irrigations, no put options, no insurance
3 Irr, Ins.: three irrigations, no put options, with insurance
2 Irr, Put, Ins.: two irrigations, with put options, with insurance
2 Irr, Put: two irrigations, with put options, no insurance
2 Irr, Put: two irrigations, with put options, no insurance
2 Irr, Ins.: two irrigations, no put options, with insurance
2 Irr: two irrigations, no put options, no insurance
D, Put, Ins.: dryland (zero irrigation), with put options, with insurance
1 Irr, Put, Ins.: one irrigation, with put options, with insurance
D, Ins.: dryland (zero irrigation), no put options, with insurance
1 Irr, Ins.: one irrigation, no put options, with insurance
D, Put: dryland (zero irrigation), with put options, no insurance
1 Irr, Put: one irrigation, with put options, no insurance
D: dryland (zero irrigation), no put options, no insurance
1 Irr: one irrigation, no put options, no insurance

is preferred across risk aversion levels and for all the scenarios examined. Despite the complexities of analyzing 16 scenarios, using SERF to interpret the data provides a clear illustration of the preferences of a decision maker.

As illustrated in Figure 1, all risk-averse DMs prefer more irrigations to less. Irrigation water in the study area is allocated annually based on reservoir storage levels, and is thus a potential limiting factor for producers (Robinson, Michelsen, and Gollehon, 2010; Stubbs et al., 2003). With an allocation of three irrigations, a put option combination is most preferred, and a crop insurance combination is least preferred. When two irrigation applications are allotted, DMs prefer additional risk management strategies of (1) purchasing both insurance and put options, followed by (2) purchasing put options only, and then (3) purchasing crop insurance only. All of these strategies are preferred over two irrigations alone.

With only one possible irrigation, DMs prefer purchasing both insurance and put options. Also with one irrigation, insurance alone is preferred over puts alone. Operating with only one irrigation and no additional risk management strategies is the least preferred of the four alternatives.

Limitations and Further Research

The study depended on data generated from CroPMan, rather than actual historical yields, to develop probability distributions for yields. Yields simulated with CroPMan cannot be adjusted for the presence of pests and diseases, which may increase with the amount of water applied through irrigation. Although CroPMan yields are not ideal, they are better in this case than relying on county average yields, as CroPMan yields better reflect farm level variability across alternative irrigation levels. Another limitation of the present study is that the put options are evaluated at expiration based on intrinsic value. A more complete evaluation would include earlier offsetting of put options, with potential time and volatility value.

Another limitation of this study is the annual nature of the irrigation decisions. The demand for irrigation is contingent on unfolding states of nature with respect to crop condition, soil moisture, available reservoir supplies, and rainfall through the growing season. While sequential modeling would have been more realistic, it would also have been considerably more complicated from a biophysical modeling standpoint. Our analysis considers the irrigation more like a pre-plant, crop mix decision, i.e., fully irrigated cotton versus deficit irrigated cotton. This approach fits in with the context of other early season decisions like buying crop insurance and forward pricing. While this abstracts from the more realistic framework of sequential irrigation decisions, it does represent the early season choice set of a Texas Lower Rio Grande Valley (LRGV) grower when reservoir levels are known and the planting-time irrigation allocations are commonly announced. Early season irrigation availability has been demonstrated to influence crop mix in the LRGV (Robinson, Michelsen, and Gollehon, 2010).

[Received December 2009; Accepted June 2011.]

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