A Risk Analysis of Alternative Crop and Irrigation Strategies Using Biophysical Simulations

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Abstract: Combining risk programming with biophysical simulation offers potential benefits for helping farmers in developing countries choose cropping and irrigation strategies or for the study of farmer behaviour. Risk can have a significant impact on the way resources are allocated and should therefore be considered in empirical studies. This study uses risk programming and biophysical simulation models to find the expected utility-maximizing irrigation strategy and crop choice for southwestern Kansas farmers. Biophysical simulation models allow the researcher to obtain yield data for a longer time period than is typically available from agronomic studies, and to study risk on a very localized level. Direct expected utility maximization is used to determine the optimal strategies. Results from the study suggest that biophysical simulation models offer a promising avenue to further understanding of the impacts of risk on farm management decisions. Because biophysical simulation models are transferable to different regions of the world, biophysical simulation can be an attractive alternative to conducting risk research in developing countries.

Introduction

Combining risk programming with biophysical simulation offers potential benefits for helping farmers in developing countries choose cropping and irrigation strategies. Risk can have a significant impact on the way resources are allocated and should therefore be considered in empirical studies. Risk arises due to uncertainty about output prices and yields because of biological lags in production, uncertain and uncontrollable weather conditions, and volatility in world grain markets. With the use of biophysical simulation models and risk programming, risk analysis can be done at substantially less cost. Research can be done on a site-specific basis without having to set up localized experiments. Cropping recommendations can then be tailored to a localized level. This paper uses risk programming and biophysical simulation models to find the expected utility-maximizing irrigation strategy and crop choice for southwestern Kansas farmers. Southwestern Kansas was used in this study so that comparisons could be made between actual experimental yields and yields generated by the biophysical simulation models.

While there has been extensive research on the allocation of irrigation water, research investigating water allocation under risk has been limited. Yaron and Dinar (1982) used a systems analysis approach to allocate water to cotton and fruit crops during peak irrigation seasons to maximize the farmer's income. Dudley, Howell, and Musgrave (1971) used an irrigation planning model and a simple crop growth model to choose acreage for irrigated crops. Yaron *et al.* (1973) examined wheat response to soil moisture and irrigation policy under conditions of unstable rainfall. Chanyalew, Featherstone, and Buller (1989) looked at the combination of irrigated maize, irrigated grain sorghum, and dryland sorghum under limited groundwater using a profit maximization model.

One of the few studies to incorporate risk into the analysis is that of Harris and Mapp (1986), who used stochastic dominance to compare water-conserving strategies for grain sorghum. Research examining irrigation strategies under uncertainty is limited due to the difficulty of finding adequate data on the risk variables. Few agronomic experiments are funded for more than five years. However, risk analysis using just five years of data would be considered highly suspect at the very least. Recently, biophysical simulation models have been refined to the point where they can produce fairly reliable yield estimates. Several studies have used crop growth models to evaluate production decisions (Mapp and Eidman, 1976; Boggess *et al.*, 1985; and Boggess and Ritchie, 1988).

Theory

Typically, agricultural firms are assumed to follow the competitive economic model with determinant input prices and quantities and uncertain output prices and yields. Deterministic economic analysis assumes that a producer is indifferent to risk. Incorporation of risk into economic analysis considers the decision maker's perception and attitude towards risk. Economists generally assume that farmers make decisions consistent with the expected utility maximization hypothesis. That is, a farmer maximizes expected utility of profit ($EU(\pi)$), where π is profit, U is a nonlinear utility function, and E is the expectation operator (Sandmo, 1971; and Iishii, 1977). The utility function is further assumed to be a concave, continuous and twice-differentiable function of profit, so that the first derivative with respect to profit is positive zero and the second negative. Because utility is ordinal, risk preferences are often modelled using the Pratt-Arrow risk aversion coefficient, which is the negative of the second derivative divided by the first derivative of the utility function with respect to profit. As the risk aversion coefficient increases, a farmer is more averse to risk.

In this study, the direct expected-utility maximization approach was used because crop yields are probably not normally distributed (Day, 1965; and Gallagher, 1987) and because possible diversification strategies were of particular interest and likely to be the strategy of choice by a risk-averse farmer. Other empirical approaches used to analyse risk have included mean-variance analysis, MOTAD, and stochastic dominance. These all have the expected-utility hypothesis as a base, and could also be used with biophysical simulation models, but the mean-variance and MOTAD analysis are based on normal distributions. The expected value of a negative exponential utility function of profit was assumed to be the decision maker's objective function. The expected utility maximization problem can be written as:

$$(1) \quad Max\ EU(\pi) = Max \sum_{i=1}^{N} p_i - e^{-\lambda\pi i}$$

$$\text{subject to: } \sum_{j=1}^{T} x_j = 1, \text{ (land constraint), and: } \sum_{j=1}^{T} r_{ij}x_j = \pi_i, \text{ for all } i$$

where π_i is the net return for outcome i, r_{ij} is total revenue minus variable cost for crop and irrigation strategy j for year i, λ is the Pratt-Arrow absolute risk aversion coefficient, the x_js are the different crop and irrigation strategies, N is the number of years, and p_i is probability of outcome i occurring. The land constraint was included so that all land was farmed.

Biophysical Simulation Models

Biophysical simulation models are mathematical models based on the biological and physical processes of daily growth. Model inputs are soil type, date of planting, plant genotype, initial soil moisture, soil characteristics, daily temperature, daily rainfall, and daily solar radiation. Because of the detailed information needed on soil type, soil characteristics, plant genotype, and solar radiation, these models are very site specific. Changing the soil characteristics will change the distribution of crop yield. Thus, results can be tailored to a localized area.

Three crop growth models, the CERES maize growth model (Jones and Kiniry, 1986), the SORGF grain sorghum model (Arkin *et al.*, 1976), and the PHOTO wheat growth model (Brakke and Kanemasu, 1979), were validated using field trials conducted at the Southwest Kansas Branch Experiment Station from 1974 to 1982 (Worman *et al.*, 1988). The predictive accuracy of each of model was checked by comparing the experimental average, maximum, and minimum yields against simulated yields. The range of yields simulated with CERES maize and the range of yields harvested from the trials were quite close. PHOTO did not perform as well; the highest simulated yield was not as high as the highest actual wheat yield.

However, the mean simulated yield was almost the same as the mean actual yield. SORGF also had some difficulty in simulating extreme yield. Furthermore, SORGF produced yields that exceeded actual yields 66 percent of the time and the mean simulated yield was 10 percent higher than the mean actual yield. The standard deviation of the simulated yields and that of the actual experimental yields were quite close for each of the models.

Also, to check the accuracy of the models, experimental yields were regressed against the simulated yield. When experimental yields are regressed against simulated yields, the slope coefficients were 0.95 for maize, 1.009 for wheat, and 0.902 for sorghum when the intercept was constrained to zero. Only the slope coefficient for sorghum was statistically different from one. Overall, all three models reasonably simulated crop yields. Other factors such as disease, insects, wind, and other stress factors not accounted for in the biophysical models could account for unexplained variation.

The validated models were used with 28 years of meteorological data to simulate yields for 28 years for 29 alternative non-irrigated and irrigated strategies defined in Table 1. The strategies included continuous non-irrigated cropping, fallow, and various levels of irrigation, ranging from 4 to 16 inches of water applied at various points in the growing season for each crop. The same soil type was assumed for all cropping strategies simulated (Worman *et al.*, 1988). The simulated yields were adjusted using the estimated slope coefficients discussed above.

Wheat is expected to be the most profitable crop, with returns over variable cost per acre ranging from \$51.89 to \$98.51 depending on the irrigation strategy (Table 2). WHT7 is the most profitable wheat production strategy. Sorghum is the second most profitable crop, with returns ranging form \$10.57 to \$57.48. SGM6 is the most profitable sorghum production strategy. Maize is the least profitable crop, with returns over variable costs ranging from –\$31.10 to \$44.73 per acre. CRN8 is the most profitable maize production strategy.

The last column of Table 2 contains a measure of skewness for the crop returns and yields. A normal distribution has a skewness measure equal to zero. Based on Table 2, several crop production strategies have skewed yield distributions.

Results

The returns over variable costs for each of the 28 years were input into the risk programming model. Five different Pratt-Arrow risk coefficients were used, ranging from 0.01 to 1.0. The mean, standard deviation, and certainty equivalent value of the portfolio are listed in the top three rows of Table 3.

The optimal crop production strategy for a farmer with a risk aversion coefficient of 0.01 (nearly risk neutral) would be to plant all acreage in wheat. WHT7 is the production strategy that would be used. A slightly more risk averse farmer (Pratt-Arrow = 0.05) would plant 31.9 percent of cropland in wheat (WHT7) and 68.1 percent in sorghum (SGM6). The expected returns per acre would drop by almost \$28 dollars per acre. The standard deviation of this portfolio is \$19.20 per acre, a reduction from \$45.59 for the most profitable. The certainty equivalent value of the portfolio is nearly \$60. If the farmer were yet more risk averse (Pratt-Arrow = 0.1), 0.5 percent of land would be in WHT3, 12.7 percent in WHT7, and 86.8 percent in SGM6. The most risk averse farmer (Pratt-Arrow = 1.0) would plant 2.0 percent of land in WHT7 and 98.0 percent in SGM6. The expected return is \$58.27 per acre with a standard deviation of \$14.67 per acre. The standard deviation is slightly larger than for the farmer with a Pratt-Arrow risk aversion coefficient of 0.5. This is due to the positive skewness measure on SGM6. Using mean-variance analysis here with skewed distributions would have produced a result inconsistent with expected utility maximization.

The shadow prices of the crops not in the optimal solution are listed in Table 3. The shadow prices are in units of certainty equivalent of income per acre. They are derived using the method found in Preckel, Featherstone, and Baker (1987). The shadow prices provide useful information for farmers considering irrigation strategies for the individual crops. As

Table 1—Alternative Cropping Strategies Considered

Variable	Maize Cropping Strategies
CRN1	4" irrigation before planting
CRN2	8" irrigation before planting
CRN3	4" irrigation in mid-July
CRN4	4" irrigation before planting, 4" irrigation before tasselling
CRN5	8" irrigation before planting, 4" irrigation before tasselling
CRN6	4" irrigation before planting, 4" irrigation before tasselling, 4" irrigation at beginning of ear growth
CRN7	8" irrigation before planting, 4" irrigation before tasselling, 4" irrigation at beginning of ear growth
CRN8	4" irrigation before planting, 4" irrigation before tasselling, 4" irrigation between tasselling ear growth, 4" at ear growth
CRN9	Maize fallow rotation
CRN10	Dryland production
	Grain Sorghum Cropping Strategies
SGM1	4" irrigation before planting
SGM2	8" irrigation before planting
SGM3	4" irrigation in mid-July
SGM4	4" irrigation before planting, 4" irrigation at 9-leaf stage
SGM5	8" irrigation before planting, 4" irrigation at 9-leaf stage
SGM6	4" irrigation before planting, 4" irrigation at 9-leaf stage, 4" irrigation at boot stage
SGM7	8" irrigation before planting, 4" irrigation at 9-leaf stage, 4" at boot stage
SGM8	4" irrigation before planting, 4" irrigation at 9-leaf stage, 4" irrigation at boot stage, 4" irrigation at flowering
SGM9	Sorghum fallow rotation
SGM10	Dryland production
	Wheat Cropping Strategies
WHT1	4" irrigation before planting
WHT2	8" irrigation before planting
WHT3	4" irrigation before planting, 4" irrigation at boot stage
WHT4	8" irrigation before planting, 4" irrigation at boot stage
WHT5	4" irrigation before planting, 4" irrigation at boot stage, 4" irrigation at soft dough stage
WHT6	8" irrigation before planting, 4" irrigation at boot stage, 4" irrigation at soft dough stage
WHT7	4" irrigation before planting, 4" irrigation at jointing, 4" irrigation at boot stage, 4" irrigation at soft dough stage
WHT8	Wheat fallow rotation
WHT9	Dryland production

Table 2—Distribution of Yields and Returns for the Alternative Crop and Irrigation Strategies

Crop	Mean Yield	Std. Dev. Yield	Mean Return[1]	Std. Dev. Return	Skewness
	bu/acre		$/acre		
CRN1	49.7	40.6	–24.89	81.19	1.47
CRN2	59.7	40.5	–15.62	80.94	1.07
CRN3	69.4	42.6	12.11	85.20	0.54
CRN4	71.0	39.3	–2.00	78.66	0.58
CRN5	78.0	38.2	–15.20	76.30	0.43
CRN6	106.9	24.8	42.59	49.69	–0.22
CRN7	110.1	22.5	34.30	45.07	0.11
CRN8	115.3	21.7	44.73	43.36	0.21
CRN9	56.6	40.7	1.54	81.48	1.17
CRN10	36.4	40.0	–31.10	80.09	1.97
SGM1	69.2	32.8	22.58	57.32	–0.31
SGM2	85.8	23.7	35.74	41.40	–0.85
SGM3	85.6	29.0	46.13	50.74	–1.39
SGM4	90.6	21.2	41.54	37.06	–1.22
SGM5	97.3	16.1	40.53	28.14	–0.81
SGM6	107.7	8.6	57.48	15.07	1.09
SGM7	108.1	8.4	47.33	14.71	1.10
SGM8	108.0	8.6	47.24	14.97	0.99
SGM9	74.9	28.1	41.81	49.25	–0.73
SGM10	46.1	31.1	10.57	54.41	0.50
WHT1	31.8	11.6	63.79	45.89	1.13
WHT2	33.6	12.2	59.77	48.24	0.89
WHT3	45.1	11.8	92.56	46.69	–0.04
WHT4	46.7	12.6	88.10	49.61	–0.05
WHT5	45.5	11.7	83.23	46.32	–0.07
WHT6	47.0	12.5	78.72	49.19	–0.09
WHT7	53.3	12.3	98.51	48.46	–0.49
WHT8	30.6	11.1	69.89	43.66	0.67
WHT9	24.4	8.3	51.89	32.75	0.95

[1]Returns above variable cost.

Table 3—Risk Programming Results for Various Pratt-Arrow Risk Coefficients

Variable	Pratt-Arrow Absolute Risk Aversion Coefficients				
	0.01[a]	0.05[b]	0.1[c]	0.5[d]	1.0[e]
Mean	98.51	70.57	62.88	58.52	58.27
Standard deviation	47.59	19.20	14.95	14.63	14.67
Certainty equivalent	86.44	59.91	53.07	43.15	41.04
	Shadow Prices for Activities Not in the Optimal Solutions[f]				
CRN1	-114.46	-106.66	-102.23	-110.83	-122.54
CRN2	-105.03	-98.61	-95.21	-106.28	-117.53
CRN3	-82.10	-80.23	-76.51	-83.96	-93.37
CRN4	-91.92	-90.19	-88.59	-103.41	-114.11
CRN5	-102.70	-99.01	-98.33	-119.05	-130.35
CRN6	-42.68	-39.67	-41.18	-64.00	-73.05
CRN7	-47.32	-39.73	-40.36	-58.25	-66.52
CRN8	-37.53	-28.40	-28.29	-41.25	-48.35
CRN9	-88.53	-82.65	-78.87	-87.37	-98.44
CRN10	-118.09	-105.86	-100.66	-109.69	-121.34
SGM1	-62.67	-57.50	-59.59	-83.59	-90.75
SGM2	-45.42	-40.15	-45.22	-69.14	-74.77
SGM3	-37.96	-40.22	-47.82	-82.74	-88.54
SGM4	-41.04	-36.86	-41.11	-59.76	-63.63
SGM5	-31.63	-13.67	-15.14	-24.52	-27.20
SGM6	-17.70	–	–	–	–
SGM7	-26.68	-6.37	-5.60	-3.27	-2.98
SGM8	-26.86	-6.72	-6.16	-4.72	-4.64
SGM9	-44.74	-42.67	-45.62	-65.52	-70.75
SGM10	-73.69	-64.05	-64.03	-81.00	-88.40
WHT1	-24.23	-11.38	-10.77	-18.11	-19.82
WHT2	-30.08	-18.43	-17.35	-20.55	-21.52
WHT3	-2.91	-0.18	–	-1.02	-1.78
WHT4	-9.01	-7.05	-6.23	-4.18	-4.47
WHT5	-12.19	-9.52	-9.35	-10.32	-11.01
WHT6	-18.32	-16.47	-15.72	-13.84	-14.10
WHT7	–	–	–	–	–
WHT8	-18.09	-3.80	-1.12	-0.74	-1.13
WHT9	-31.20	-13.78	-12.52	-20.78	-23.23

[a]Optimal portfolio: *WHT7* = 100 percent.
[b]Optimal portfolio: *WHT7* = 31.9 percent, *SGM6* = 68.1 percent.
[c]Optimal portfolio: *WHT7* = 12.7 percent, *WHT3* = 0.5 percent, *SGM6* = 86.8 percent.
[d]Optimal portfolio: *WHT7* = 2.5 percent, *SGM6* = 97.5 percent.
[e]Optimal portfolio: *WHT7* = 2.0 percent, *SGM6* = 98.0 percent.
[f]In units of certainty equivalent per acre.

a farmer gets more risk averse, the wheat fallow strategy (WHT8) becomes more attractive. Thus, under some price combinations, it is likely that wheat fallow would be in the optimal solution. SGM7 continues to be more attractive for more risk-averse strategies because the penalty cost continues to decrease as risk aversion increases. Full irrigation of sorghum is a risk-reducing strategy for sorghum, whereas no irrigation of wheat is a risk-reducing strategy for wheat. CRN8 in all cases has the smallest penalty cost for maize for inclusion in the optimal portfolio. Given different price expectations where maize is relatively more profitable, CRN8 would be the maize strategy most likely to be used.

The results illustrate that crop simulation models can be useful in generating distributions of yields over a longer time frame for risk analysis. Checking distributions generated by biophysical simulation models with actual experimental data suggests that yield distributions generated with biophysical simulation models do not differ greatly from experimental data. The results also show that the yields can then be input into risk programming models to take economic behaviour into account.

In addition, calculating certainty-equivalent values for those cropping activities that do not enter the optimal portfolio can further help producers understand the consequences of different cropping and irrigation strategies. These shadow prices can then be useful for altering recommendations as market conditions change.

Conclusions

This study used biophysical simulation models and risk programming to investigate alternative crop production and irrigation strategies. The biophysical simulation models were used to generate crop yields based upon historical weather patterns. The simulation models were used because time-series data are often not available for a long enough period to use risk analysis. Comparing simulated yields to actual experiment station yields suggests that the simulation models perform reasonably well.

Risk programming was used to investigate the crops and irrigation strategies that maximize expected utility of income for a risk-averse farmer. Direct expected utility maximization was used because yield distributions and incomes were skewed. Direct expected utility maximization also allows for a detailed interpretation of shadow prices on those crops and irrigation strategies that do not enter the optimal portfolio.

The results from the paper suggest that biophysical simulation models may be useful for risk analysis. These models are able to use historical weather data to project crop yields in the past. Because of the nature of agronomic experiments, insufficient data are usually available for risk analysis. Biophysical simulation models offer a promising avenue to further understanding of the impacts of risk on farm management decisions.

Note

[1]Kansas State University.

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Discussion Opening—*Chung L. Huang* (University of Georgia)

Various risk models and mathematical programming techniques have been developed to address risk and uncertainty in decision making involving crop production, pest management strategies, farm programmes, and rural bank portfolio behaviour. A common feature of these economic analyses is the incorporation of the decision maker's perception and attitude towards assuming risk into the framework of expected utility maximization hypotheses for modelling expectations of possible outcomes and their probabilities. Methodologically, a wide range of approaches has been used to solve decision-making problems involving risk and uncertainty of future events, varying from using conservative estimates for the uncertain elements to methods that explicitly incorporate probability density functions for the uncertain parameters. More recently, plant growth simulation models that consider the interactions of stochastic weather conditions, soil type, plant growth, moisture stress and irrigation decisions within an integrated bioeconomic framework have become important research tools. The present paper contributes appropriately to this class of growing risk analysis literature.

While the paper can be considered as generally outstanding, it lacks explanation of the theoretical model and methodology used. The paper only indicates that the decision maker's objective function was maximized assuming a negative exponential utility function of profit. The forms of the utility function represent different attitudes towards risk. The specification of the model implies that the decision maker is risk averse and has an attitude towards risk unrelated to wealth. It is not clear why this is the case. Although the probabilities of possible outcomes for different production strategies were explicitly incorporated in the objective function, there is no explanation of how the probability function was derived. Most importantly, the model assumes a profit-maximization framework. We all know that prices influence farmers' decisions, especially production adjustments. In the short run, farmers adjust by changing current inputs; in the longer term, solutions come by changing technologies and scale dimensions. It is not clear how price variations among crops and over time were considered in the formulation.

The authors rightly point out that biophysical simulation models are plant genotype and location or site specific. Any changes in input data such as soil characteristics result in different distributions of crop yields. Thus, it is suggested that the application of biophysical simulation models offers the advantage of transferability to different regions of the world and the capability of generating distributions of yields over a longer time frame for risk analysis. Given its site-specific nature, it seems that some sensitivity analyses reflecting differences in soil and weather should be performed to measure the stability of model results. In fact, the requirement of very detailed and specific input information would be an obstacle that limits the transferability. In the absence of experimental data, I wonder how the researchers would validate and calibrate the performance of the simulation models. Furthermore, if the growth simulation models are sensitive to plant genotype, then changing cultivars would appear to render the generation of yields distribution over a long period of time unnecessary or invalid.

More specifically, the results show no differences between risk aversion coefficients of 0.5 and 1.0, and they should be reported as such. Apparently, many farm plans are similarly organized. Hence, changes in risk aversion coefficients between 0.5 and 1.0 do not reduce net return or entail changes in the optimal portfolio.

The authors are to be commended for the enormous efforts devoted to bridging the gap between economic analysis and biophysical simulation techniques in an application to determine optimal crop choice and irrigation strategies.

[Other discussion of this paper and the authors' reply appear on page 119.]