An Empirical Evaluation of Irrigation Insurance for Agricultural Systems in the Mexican Northwest

Akssell J. Leiva* and Jerry R. Skees**

* Consultant for GlobalAgRisk Inc and Former Research Assistant in the Department of Agricultural Economics of the University of Kentucky.

** HB Price Professor of Policy and Risk. 310 Charles E. Barnhart Building, University of Kentucky, Lexington, Kentucky 40546

Selected Paper prepared for presentation at the Canadian Agricultural Economics Society – Canadian Economics Association joint Annual Meeting, Montreal, Quebec, May 25-28, 2006.

The authors wish to express their appreciation to Comision Nacional del Agua (CNA) in Mexico City and the Sociedad de Responsabilidad Limitada (SRL) del Rio Mayo in Navojoa, Sonora for providing the data and information for this paper. We are also grateful to Roy Black for his helpful insights. Finally, we thank the Inter-American Development Bank and GlobalAgRisk Inc. for supporting this research.

An Empirical Evaluation of Irrigation Insurance for Agricultural Systems in the Mexican Northwest

Abstract

Prototype inflow-based derivative contracts are designed to hedge irrigation risk in the Rio Mayo Valley of Sonora, Mexico. The results indicate that an 18-month contract is feasible given the specific characteristics of the region selected for the study.

Introduction

Regions of the Mexican Northwest are characterized by scarce precipitation, and rely almost entirely on reservoir systems to irrigate large cropping areas, provide water to urban centers, and even generate electricity. Irrigation, however, remains the most water-intensive sector of those regional economies. In fact, in the dry states of Sonora, Sinaloa, and Baja California, irrigation takes up a high percentage of total water consumption (CNA). Despite the existence of irrigation systems, farm income is by no means shielded from weather uncertainties since the availability of water depends to a large extent on river inflows – a highly variable hydrological variable. When the annual accumulation of inflows is not adequate to replenish the reservoirs, agriculture is the sector that bears the major water cuts; consequently, cropping activities decline, rural unemployment increases, and farm income falls. Put differently, the annual variability of reservoir inflows represents the most important source of production risk for irrigated agriculture in these Mexican localities. Therefore, research that investigates potential risk management solutions is relevant not only from a purely academic viewpoint, but also from a policy perspective.

Economists have recognized that the uncertainty surrounding reservoir inflows stymies the operation and management of irrigation districts. One body of literature has focused on the technical operation of reservoirs and proposed the use of several optimization techniques to develop reservoir operation policies that account for the stochastic nature of inflows [see Labadie for a recent survey]. Among the methods studied are stochastic dynamic programming (Dudley and Burt; Kelman el al; Stedinger, Sule, and Loucks), chance-constrained programming (Eisel), and chanced-constrained dynamic programming (Askew). These tools have been used since the 1960s to design the optimal size of irrigation districts, and to operate corresponding reservoirs. Although with these tools operators are better prepared to assess the impact of stochastic inflows, their application implies some opportunity costs and seldom guarantees a full risk-sharing solution. As Dudley (1988a) puts it "why use stored water as an insurance medium when it evaporates and its presence in the reservoir increases reservoir spills." Dudley suggests that storing output and revenues should also be included in the set of decision variables of reservoir operation models.

Another body of literature has explored institutional approaches that rely on water markets and financial contracts to facilitate water allocations under uncertainty conditions. The institutions proposed include: developing option contracts and water markets to transfer irrigation supplies to urban centers (Michelsen and Young; Taylor and Young); interruptible water markets between power companies and agriculture (Hamilton, Whittlesey, and Halverson); contracts to divert agricultural use towards ecological uses (Turner and Perry); sharing the capacity and volume of a reservoir (Dudley); and using a water bank (Iglesias, Garrido, and Gomez-Ramos). Furthermore, emerging research has focused on transferring new financial innovations to the management of weather risk in agriculture (Turvey; Hao, Hartell, and Skees; Skees and Enkh-Amgalan; Skees et al); however, research on the use of these innovations to hedge the income risk caused by stochastic reservoir inflows remains lacking, except for a few instances (Skees and Zeuli).

This paper uses data from the Rio Mayo irrigation district to examine the feasibility of using an inflow-based derivative as primary insurance against water supply risk in irrigated agriculture. The analysis uses stochastic simulations to develop a set of risk management strategies that combine an inflow-derivative with reservoir operation policies, including pricing considerations. Moreover, a ranking procedure is employed to evaluate the simulated income distributions produced by each strategy according to the buyer's risk preferences and downside risk measures. The framework developed in this paper, and insights derived from it, are relevant to decision makers, irrigators, and organizations interested in risk management strategies for irrigated agriculture.

Irrigated Agriculture in the Mayo Valley

Description

The Rio Mayo irrigation district is located in the southern part of the state of Sonora. The district includes an area of 98,598 ha suitable for irrigated agriculture, and groups 11,717 irrigators under 16 irrigation modules. The main source of water supply for the irrigation district is the watershed of the Mayo River (hence the name Rio Mayo), which covers an approximate area of 11,000 km^2. The river extends for approximately 350 km and averages 1,000 million m^3 in annual streamflows. The hydraulic work used to secure the flows from the river is the Alfonso Ruiz Cortinez (ARC) reservoir, which has a storage capacity of approximately 1,200 million m^3. Approximately, 81% (825 million m^3) of the water supply is used for irrigation, while the rest is allocated to other uses or lost due to evaporation. Please refer to Table 1 for descriptive statistics about the Rio Mayo.

The agricultural cycle in the Mayo Valley, as in other parts of the Mexican Northwest, is divided in two cropping seasons, namely Fall-Winter (FW) and Spring Summer (SS). On average, irrigators plant 100,000 ha in year, with 75% of the planting taking place in FW and 25% in SS. In terms of cropping patterns, the FW season (Figure 1) carries the entire production of wheat, which is the main crop of the region, in addition to a substantial proportion of maize and safflower. In contrast, the SS season (Figure 2) has a variable crop pattern, but cotton and safflower are the dominant crops. The relative importance of the FW season is also reflected in the fact that, on average, the ARC reservoir stores 255 million m^3 (52%) more in October (beginning of FW season) relative to April (beginning of SS).

Organization and Decision-Making

The Water Law of 1992 introduced reforms that had an impact in the organization and operation of irrigation districts in Mexico, including the Mayo Valley [see Naylor, Falcon, and Puente-Gonzalez, (2001) for more details on policy reforms]. Currently, there are three parties that jointly plan, distribute, and use water for irrigation purposes: the National Water Comission (CNA), the Limited Responsibility Society (SRL), and the irrigation modules. CNA is an autonomous government agency of the Mexican federal government in charge of regulating all aspects of water use and planning, including the operation of reservoirs and issuance of water concessions. On the other hand, irrigation modules are subdivisions of an irrigation district that represent their individual members in the decision-making process and also participate in the water allocation process. In turn, the SRL groups all the irrigation modules and is responsible for collecting fees to finance the operation the management of the irrigation district.

In a typical irrigation cycle, the decision-making process starts when irrigators submit their individual irrigation plans to their corresponding irrigation module. In turn, the irrigation modules, the SRL, and CNA meet to estimate the water required to implement the irrigation plans, given the storage conditions in the ARC reservoir as of October 1. Although some negotiations may occur, CNA is the main decision maker about the annual release or supply of water. In times of drought, however, CNA's decisions may entail strict modifications in irrigators' cropping plans to accommodate irrigations supplies. At any rate, once water is released from the reservoir, the SRL receives and allocates the endowment of water to each irrigation module. Finally, the irrigation module delivers water to the parcels to be irrigated by individual irrigators.

The Impact of Water Shortage

In a place where the mean annual rainfall is only 260 mm (10.24 in), water is the most limiting factor in agricultural production. Figure 3 shows that there is a strict relationship between the annual plantings and the annual volume of water from the ARC reservoir made available for irrigation. For instance, in the year 1987-1988 when the agricultural sector received the lowest allocation of water (481 million m^3) in the historical series, the irrigation district registered the lowest number of hectares planted (70,202 ha). However, the effect of water shortages in the Mayo Valley has been more evident in the last four years when the annual plantings have declined to about 80% of the historical mean.

Overview of Empirical Procedures

A stochastic dynamic simulation model is employed to assess the potential for using an inflow-based derivative in the Mayo Valley. The stochastic part of the model is based on the simulation of the random process that underlies the seasonal inflows feeding the ARC reservoir. In addition, the model is composed of a set of reservoir operation policies or releases rules. The third and most important component is the contract design. In particular, several designs are integrated to the model and the resulting plantings cumulative distributions are ranked according to a risk preference procedure. Each component is briefly explained below.

Inflow Simulations

The streamflows of the Mayo River are defined by seasonal changes. Figure 4 shows the mean monthly inflows for three selected periods for which data is available. The figure shows two important details that play an important role in the simulation. First, notice that most of the inflow accumulations take place in the SS season, particularly within the months of June and September. Second, the figure shows that although FW accumulations carry less weight, during the December-January months the inflows experience a small "bump." In fact, the data shows that some years when the "bump" is large enough, the FW winter accumulation might be just as important as the SS accumulations. Rio Mayo farmers have recognized the value of those "bumps" to irrigate land during the SS season, and increase their revenues.

In order to simplify the simulation, the monthly inflows were grouped in seasons corresponding to the agricultural cycle of the Rio Mayo irrigation district. Specifically, the FW accumulation period includes inflows from October to March and accounts for

35% of annual accumulations, while the SS accumulation period includes inflows from April to September and accounts for 65% of annual accumulations. Furthermore, there is a positive correlation of 0.23 between FW and SS inflows.

The random process governing the random seasonal inflows was simulated using a multivariate empirical (MVE) distribution. The advantage of the MVE distribution is that it preserves the intra-year correlation structure in a satisfactory manner (Richardson 2003). Table 2 compares the results of the simulation against the actual data for the seasonal inflows. Furthermore, statistical tests suggest that the mean and covariance of the simulated data correspond to those of the actual data.

Reservoir Operation Policy and Planting Response Functions

For a given volume of water, the agricultural output produced in an irrigation district depends on how water from the reservoir is operated (e.g. release decisions) and on the set of characteristics that determine the relationship between water and crop output (e.g. conveyance efficiency, temperature, distance, etc). One the one hand, although the reservoir operation policies used by CNA were provided to the authors, they did not produce results that matched the actual data on released volumes. Therefore, we relied on the hydrological data, the historical plantings, and the experience of Rio Mayo irrigators to derive the reservoir operation rules. The reservoir operation policy used for the simulation is based on the assumption that the marginal value product of water in the FW season is greater than in the SS, therefore for a given level of water in the reservoir irrigator will prefer more water to be allocated to FW rather than SS. On the other hand, there are physical and climate factors that suggest that the volume of water released from the reservoir leads to less than proportional increments in the number of hectares planted within a given season. Therefore, response functions for both seasons were developed that incorporated diminishing marginal returns to the use of irrigation water[1].

Using the reservoir operation policy and the plantings response functions, the simulation yields results (i.e. planted hectares) that are not statistically different from the observed historical data. For instance, the FW historical records suggest that plantings are typically 75,900 ha and for the same period the simulation yields mean plantings of 73,160 ha. Similarly, the SS historical data indicates that the mean plantings are 28,000 ha and the mean simulated plantings are 27,745 ha.

Contract Designs

In this study we examine the feasibility of contracts that derive their value from the inflows of the Mayo River as measured in the site that feeds the ARC reservoir. In addition, the contracts are structured as option-type arrangements in which the buyer is entitled to a payment when the inflow index falls below some pre-determined strike value. In terms of pricing, two factors determine the full price the buyer will be charged: the “pure” premium and the loading factor. The pure premium is computed on the mean payment that the seller of the contract can expect to make in the long run. In turn, the pure premium is loaded with a 50% mark up to account for other factors that a potential

[1] The combination of reservoir operation policies and response functions that matched the actual management decisions and economic outcomes are presented in the following equations:

$$RFW = 187 - 0.005Stor\_Oct1 + 0.02(Stor\_Oct1)^{1.5}$$
$$RSS = 0.87Stor\_Apr1$$
$$PlantingFW = -21{,}000 + 380RFW - 8.8(RFW)^{1.5}$$
$$PlantingSS = -12{,}000 + 245RFW - 5.6(RFW)^{1.5}$$

Where RFW and RSS refer to releases in FW and SS, respectively; Stor_Oct1 and Stor_Apr1 represent the volume of water stored in the ARC reservoir as of October 1 and April 1, respectively; PlantingFW and PlantingSS refer to the hectares irrigated in FW and SS, respectively.

seller may consider when operating in a new market (e.g. administration, return on investment, uncertainty, reserves loading, etc.).

In this study two basic types of contracts are considered and their difference lies in the period over which the inflow index is used to compute the payments and the number of triggers that determine the contract structure. The first type of contract is based on a 12-month inflows accumulation period and a single strike value to trigger the payments. Furthermore, by extending the accumulation period to 18 months and introducing multiple strike values in the structure of the payment-triggering rule a second type of contract is considered. While the second contract is more complex, it comes with the benefits of tailoring the contract more effectively to the "bumps" identified in Figure 4. Whenever the "bump" is large enough, farmers obtain a higher-than-expected increase in the water supply, which allows them to increase their plantings during the SS season.

The general structure of the put contracts is stated in equations 1, 2, and 3 below. Equation 1 describes the maximum payoff or indemnity paid by the contract, measured in hectare-equivalent income[2], in a given year, denoted by $\overline{P}_t$. This maximum payment is a function of the first trigger and the volume of inflows accumulated throughout the previous time period, denoted by I_C and I_{t-1}, respectively. The indemnity rule is linear and pays only when the I_{t-1} accumulation falls short of the critical level represented by I_C. Furthermore, the contract pays a TIC of 100 units of hectare-equivalent income for each m^3 that falls short of the critical level of inflows I_c.

[2] Since data on costs of production and crop prices were not obtained, income and payoff from the contract will be approximated using a hectare-equivalent measure. In other words, annual plantings, rather than annual income, will be the basis for comparing the risk-return profile of the risk management strategies developed in the study.

$$\overline{P}_t = TIC \times \begin{cases} 0 & if\ I_{t-1} > I_C \\ \\ (I_C - I_{t-1}) & if\ I_{t-1} < I_C \end{cases} \tag{1}$$

In addition, equation 2 represents a discount rule that applies when the contract includes more than one time period (more than 12 months). In other words, the actual payment P_t received in a given year is equal to the maximum qualifying payment $\overline{P}_t$ discounted by the factor D. The discount factor D is computed according to equation 3 and can take any value in the interval [0,1]. In particular case studied, the maximum payment $\overline{P}_t$ (computed using equation 1) is discounted if the volume of FW inflows accumulated in the second time period (i.e. October-March), denoted by $I_{1,t}$ falls within the bounds of the upper and lower triggers, denoted by $I_{\max}$ and $I_{\min}$, respectively. If $I_{1,t}$ falls short of the lower bound trigger, no discount rule applies and the contract pays exactly $\overline{P}_t$. However, if $I_{1,t}$ exceeds the upper bound trigger then the contract makes no payment.

$$P_t = \overline{P}_t * D \tag{2}$$

$$D = 1 - \begin{cases} 1 & if\ I_{1,t} \geq I_{\max} \\ \left(\dfrac{1}{I_{\min} - I_{\max}}\right) \times \left(I_{\min} - I_{1,t}\right) & if\ I_{\min} < I_{1,t} < I_{\max} \\ 0 & if\ I_{1,t} \leq I_{\min} \end{cases} \tag{3}$$

While the 12-month contract is straightforward, the 18-month contract may be better described with an example. Suppose the following parameters: I_c = 725, TIC = 100 ha. Then, if the inflows corresponding to the period agricultural year 2005-2006 were 550 million m^3, then maximum payment would be 17, 500 ha.[3] However, if inflows of 300 million m^3 were registered in the period October 2006 to March 2007, then the payment would have to be discounted[4] to 50% of the maximum payment, which is 8,750 ha.

Results and Discussion

A set of possible contracts was structured by setting specific values to the parameters described in equations 1 and 3. In the case of equation 1, the following three values for the trigger I_c were selected: 700, 750, and 800 million m^3, which represent 70%, 75%, and 80% of mean annual inflows. These parameters in equation 1 fully describe the structure of the single period or 12-month contract described above and represents the 12-month component of the multi-period contract. In the case of the multi-period contract or 18-month contract, the following trigger values were selected for equation 3: 100 and 200 million m^3 for I_{min} (equivalent to 27% and 54% of the mean FW inflow accumulations, respectively); 300 and 500 million m^3 for I_{max} (equivalent to 81% and 135% of the mean FW inflow accumulations, respectively).

Table 4 describes a set of 12 possible strategies that could be implemented in Rio Mayo irrigation district to hedge against irrigation risk. Each strategy is identified by the three parameters in the following format: I_c-I_{min}-I_{max}. For instance strategy 700-100-300 denotes an 18-month contract that uses an I_c trigger of 700 million m^3, an I_{min} of 100 million m^3, and an I_{max} of 300 million m^3. The base case scenario, or case in which no risk management is used, is presented to establish a benchmark and compare the results from the set of strategies. In addition to mean income produced by each strategy, table 4 reports certain criteria to measure the risk profile of each strategy, including the

[3] $\overline{P} = (725 - 550) \times 100\, ha = 17{,}500$

[4] $D = (1 - (-0.0025) \times (-200)) = 0.5$, supposing I_{min} = 100 and I_{max} = 500.

coefficient of variation (CV), value-at-risk probabilities (VaR), and conditional value at risk (CVaR)[5]. The latter measures assume that the maximum income shortfall that the irrigation district tolerates within a given year is only 25% of mean income. In other words, we assume that shortfalls below 75,000 units of hectare-equivalent income impose tremendous burdens to the irrigation district.

As reported in table 4, without any insurance strategy, the mean hectare equivalent income is 98,853 units and a relative income variation of 20.24% around the mean (coefficient of variation or CV). In addition, under the base scenario there is a 13% chance that income falls below the 75,000 ha threshold and the expected shortfall is approximately 8,342 units of hectare-equivalent income. As with any risk-sharing mechanism, adopting any of the risk management strategies implies that decision makers are willing to give up a fraction of their expected income to reduce their risk exposure. For instance, with a single-period or 12-month contract that starts to pay when the annual accumulation of inflows falls below 750 million m^3, the expected annual income is reduced to 96,017 units; however, the variation of income is reduced to 18.27% as measured by the CV, while the probability of falling short of the 75,000 units threshold declines to 11.2%, with mean shortfalls averaging 7,442 units.

The results reported in table 4 also indicate that the 18-month contract seems to achieve a higher risk reduction at a more affordable price or premium. For instance, the 800-00-00 contract costs 7,486 units of income and reduces the income variation to

[5] VaR and CVaR are measures of downside risk. Typically, VaR refers the maximum loss or threshold for a given confidence level during a specific period of time. In the particular application we use the cumulative probability distribution to compute not the maximum loss, but the probability that the annual income falls below a given threshold. In other words, wee seek the probability value, given a certain tolerable threshold. While VaR provides the probability of income falling below the desired threshold, CVaR measures the mean value of the expected shortfall. In our case, the CVaR measure represents the mean value of the hectares below a given threshold.

18.34%, the VaR probability to 11.4%, and the CVaR measure to 7,529 units of hectare equivalent income. Conversely, the 800-100-300 costs 3,275 units of income (only 44% of the cost of the 800-00-00 contract) and reduces the CV measure to 16.45%, the VaR probability to 6.3%, and the CVaR measure to 3,275 unit of income. As depicted in figure 4, the months of December and January experience a "lump" in the supply of water that feeds the ARC reservoir. However, during certain years the "lump" is large enough to replenish the reservoir before the full replenishment of the SS season starts. In the cases of large "lumps" the irrigation district has the ability to generate additional income from the extra plantings that result from the unexpected increase in the water supply. Since the 18-month structure takes the "lump" factor into account, the contract is better tailored to the particular conditions of the Rio Mayo system. In particular, the discount factor introduced in equations 2 and 3 recognize the fact that the need for insurance payments is reduced when a large "lump" augments the supply of water; consequently, the insurance premium is reduced and the contract becomes more affordable.

Comparison across the summary statistics of the proposed contracts is of little help without a mechanism to weight the risk-return tradeoff implied by the strategies. For instance, if the decision makers would be interested in the most affordable alternative, the clear choice is the 700-100-300 contract costs only 1,802 units of income and effectively reduces the risk exposure as measured by the three risk measures. However, if the decision maker was more sensitive to risk, the 800-100-300 contract provides the greatest protection, but costs about 1,472 units of income more than the 700-100-300 contract (i.e. an 81% increase in price for a little bit more of insurance coverage).

In the literature the most common method used to rank risky scenarios is stochastic dominance, although the mean-variance approach has also found some popularity. However, in this paper we use a new method proposed by Hardaker *et al* (2004) called stochastic efficiency with respect to a function (called SERF hereafter)[6]. SERF ranks risky alternatives using their certainty equivalents (CE) over a defined range of risk aversion measures. In practice, the SERF is applied when the utility function selected to approximate the decision maker's risk preferences has an inverse function that can be computed based on ranges in the risk aversion coefficient (RAC). Furthermore, the SERF method possesses the following advantages: it produces a smaller efficient set than its stochastic dominance counterpart; it provides a cardinal measure of the decision maker's conviction for risk alternatives at each measure of risk aversion utilized.

While some studies usually elicit risk attitudes directly from decision makers or incorporate those estimated in other studies in the same location, we did not engage in any activity to gauge the risk preferences in the Rio Mayo area nor we found any previous study to use as a guide. Therefore, we decided to approximate the unknown risk preferences from the collective group of farmers in the Rio Mayo by means of a power utility function[7]. Furthermore, the power utility function is suitable for use in the SERF method proposed by Hardaker *et al* (2004). In addition, the analysis relies on the relative

[6] SERF possess several advantages over generalized stochastic dominance, however the discussion of those ranking methods is outside the scope of this paper. Readers are referred to the Hardaker *et al* (2004) article for a full comparison between the methods.

[7] The analysis is based on a power utility function that exhibits constant relative risk aversion (CRRA). The CRRA property is convenient to group all decision makers in the irrigation district regardless of their wealth levels. Furthermore, since wealth in this paper is measured in "hectares", the CRRA property allows for preferences to remain unchanged when all the payoffs are converted to a monetary unit by multiplying by the appropriate per hectare returns. Specifically, utility is given by $u = \frac{1}{(1-R_r)} w^{(1-R_r)}$, where R_r refers to the relative risk aversion coefficient.

risk aversion measures proposed by Anderson and Dillon (1992), which range from a RAC of 0.5 for slightly risk aversion to a RAC of 4 for extremely risk aversion.

The entire set of risk management alternatives is presented in Figure 5a. For each contract design the figure displays the certainty equivalent (hereafter CE) for each RAC within the range proposed by Anderson and Dillon (1992). Once the CE corresponding to each strategy is plotted against the CE from other strategies, the SERF efficient set is found by identifying the locus with the maximum CE values for a given RAC. For instance, Figure 5a clearly identifies that strategies 800-00-00 and 750-00-00 are the least preferred strategies for any level of risk aversion, while strategy 750-00-00 is dominated by all strategies with the exception of the 800-200-500 contract at very low levels of risk aversion. One reason behind this result is the 12-month contracts achieve risk-reducing results comparable to the 18-month contracts, but charge considerably higher prices, as presented in table 4.

The SERF efficient set is presented in Figure 5b, which contains only following four strategies. Thus, for decision with RAC less than 1.52, the preferred strategy is the base case scenario. In other words, hardly to normal risk averse individuals (RAC between 0.5 and 1.5) prefer to self-insure using the reservoir operation policy to hedge against irrigation risk. Nonetheless at RACs greater than 1.52 the SERF efficient set contains only strategies that make use of the risk-sharing mechanism. For instance, modest risk-averse decision makers will prefer to use strategy 700-100-300 to manage water supply risk. As the level of risk aversion increases to higher levels, the SERF includes strategies 750-100-300 and 800-100-300. The fact that only 18-month contracts are included in the SERF efficient set reinforces the notion that contracts that take into account the higher-than-expected inflows that the Mayo River yields between December and January provide more cost-efficient income stabilization to farmers.

The CE values of the SERF efficient set are presented in Table 5 for five levels of risk aversion. Using the differential in CE values measures the degree of conviction for the preferred strategies. For instance, slightly risk-averse decision makers would need to be paid a minimum between 616 and 1,229 units of income to buy the insurance (i.e. a subsidy). In turn, for moderate to extremely high levels of risk aversion, decision makers would need to be paid a certain amount to switch away from the preferred insurance strategy. For example, at modest risk aversion level, a sure minimum payment of 433 units of income for farmers to give up the 700-100-300 contract to no hedging at all; while at very high risk aversion, the sure payment would need to be 1,405 units of income to forgo the 750-100-300 contract relative to no hedging.

Conclusion

This paper has introduced the use of prototype risk-sharing contracts in the Rio Mayo irrigation district. We conclude that these types of contracts have a promising potential to mitigate economic consequences of uncertain water availability in the Mayo Valley, particularly in reducing the downside risk in the income profile of farmers. More importantly, even when the prices of contracts have been marked up by 50%, the premium rates remain under the 10% mark, which indicates that they could be affordable from a buyer’s point of view. Affordable premium rates not only increase feasibility of a potential risk-sharing market in Mexico, but also reduce the need for government sponsorship to encourage farmer participation.

Although two types of contracts were considered, we conclude that the 18-month contract is more effective in providing risk-reducing results at the most affordable rates. In particular, the risk ranking analysis indicates that the most attractive contracts for risk-averse decision makers are very affordable with risk premium rates ranging from 3.9% to 6.9%. However, one of the disadvantages of the 18-month contract is that after paying the insurance premium, farmers would have to wait 18 months to receive the indemnity payment, when they qualify for it. One of way to shorten the waiting period could be to introduce partial payments after the first 12-month sub-period has elapsed.

Table 1 Descriptive Statistics of Hydrological and Economic Characteristics of Rio Mayo Irrigation District

	Inflows[a]	Release[a]	FW Storage[a,b]	SS Storage[a]	Annual Plantings[c,d]	FW Plantings[c,e]	SS Plantings[c,e]
Mean	1,013.19	825.43	743.48	488.81	101.05	75.97	28.19
Standard Error	64.79	28.90	32.39	45.13	3.65	1.54	4.07
Median	914.50	824.70	685.00	415.39	99.24	78.86	20.62
Standard Deviation	453.52	202.30	226.74	315.92	0.22	8.41	22.30
Minimum	454.73	440.88	314.80	25.11	51.81	49.72	0
Maximum	2,511.51	1,240.41	1,206.32	1,124.56	142.46	85.64	72.66

Notes: Data collected from CNA and SRL
a: inflows, releases and storage are measured in million m^3 (1 cubic meter = 0.0008107 acre foot = 35.315 cubic foot) for the period 1955-2004
b: storage as of October 1 (beginning of agricultural cycle)
c: production measured in thousand hectares (1 hectare = 2.47 acre)
d: Period 1969-2003
e: Period 1973-2003

Table 2 Statistical Properties for Simulated and Historical Data

Variable	Means	Covariance	
		Historical Series	
		FW	SS
FW	369.8	111,631.6	18,934.3
SS	664.5	18,934.3	53,971.7
		Simulated Series	
		FWSIM	SSSIM
FWSIM	360.2	87,207.6	19,468.5
SSSIM	662.9	19,468.5	58,768.8

Note: FW and SS represent the historical inflow accumulations corresponding to the periods of October-March and April-September, respectively. FWSIM and SSSIM represent the MVE simulated inflows corresponding to the periods of October- March and April-September, respectively.

Table 3 Distribution Comparisons of Simulated and Historical Inflow Data

	Test Value	Critical Value	P-Value	Conclusion*
2 Sample Hotelling T^2 Test[a]	0.03	9.58	0.984	Fail to Reject H_0
Box's M Test[b]	1.21	11.34	0.750	Fail to Reject H_0
Complete Homogeneity Test[c]	1.19	15.09	0.946	Fail to Reject H_0
Correlation Matrix Test[d]	0.19	2.69	-	Fail to Reject H_0

* 99% level of confidence.
[a]H_0: Mean vectors are the same.
[b]H_0: Covariance matrices are equivalent.
[c]H_0: Mean vectors and covariance matrices are equivalent, respectively.
[d]H_0: correlation matrices are equivalent.

Table 4 Summary Statistics from Insurance Alternatives in Rio Mayo Irrigation District

Strategy[a]	Mean Income[b]	CV[c]	VaR[d]	CVaR[e]	Premium[f]	Premium Rate[g]
Base	98,853.90	20.24	13.0%	8,342.59	NA	NA
700-00-00	96,789.95	18.39	13.1%	8,879.51	4,115.56	8.8%
750-00-00	96,017.97	18.27	11.2%	7,442.1	5,654.91	11.3%
800-00-00	95,099.59	18.32	11.4%	7,529.2	7,486.18	14.1%
700-100-300	97,950.14	17.80	8.5%	5,774.09	1,802.10	3.9%
750-100-300	97,617.39	17.14	7.3%	4,942.17	2,465.62	4.9%
800-100-300	97,211.54	16.45	6.3%	4,228.43	3,274.89	6.1%
700-100-500	97,716.22	17.56	9.1%	6,173.49	2,268.56	4.9%
750-100-500	97,288.88	16.87	8.0%	5,398.62	3,120.67	6.2%
800-100-500	96,772.36	16.14	7.3%	4,899.07	4,150.63	7.8%
700-200-500	96,486.17	16.08	7.7%	5,140.92	4,721.29	8.9%
750-200-500	97,075.36	16.76	8.5%	5,724.94	3,546.44	7.1%
800-200-500	96,486.17	16.08	7.7%	5,140.92	4,721.29	8.9%

Notes:
NA: Does not apply.
a: Each strategy is coded according to the following format (strike, I_{min}, I_{max}). Please refer to equations 1, 2, 3 for more explanation on the parameters of each contract.
b: Measured in hectare equivalents.
c: Coefficient of Variation (in %).
d: Value at Risk evaluated at the 75,000 ha threshold (in %).

e: Conditional Value at Risk at the 75,000 ha threshold in hectare equivalents.
f: Insurance premium with a 50% mark up, expressed in hectare equivalent income.
g: Premium rates as a percentage of the maximum indemnity.

Table 5 CE Values of the SERF Efficient Set for Across Risk Aversion Levels

	Risk Aversion Levels				
Strategy	Very Low	Normal	Moderate	High	Extreme
Base	**97,772.88**	**96,790.71**	94,354.15	91,733.47	88,976.42
700-100-300	97,156.73	96,455.37	**94,787.09**	93,079.94	91,337.76
750-100-300	96,887.09	96,242.39	94,710.66	**93,139.34**	91,521.97
800-100-300	96,543.99	95,954.67	94,554.15	93,112.23	**91,615.92**

Note: Bold indicates highest CE for risk aversion level

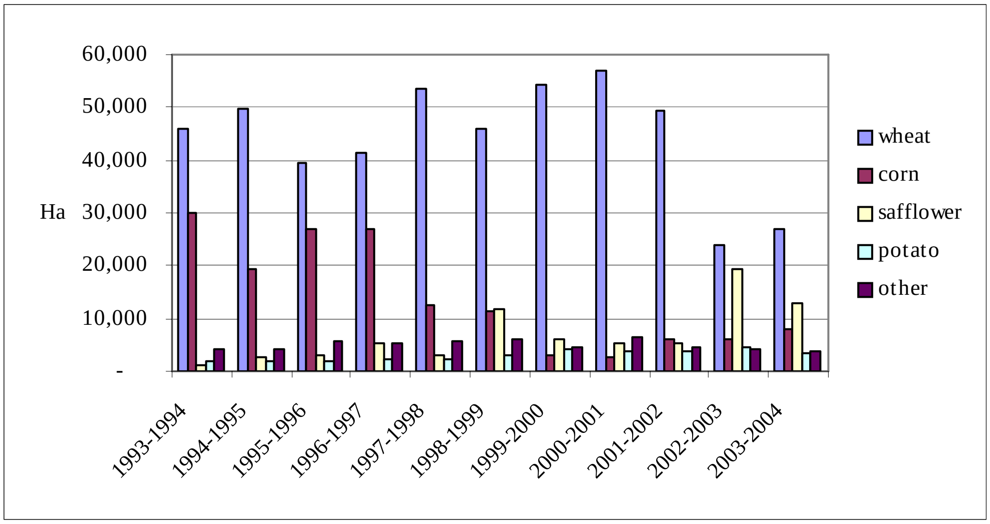

Figure 1: Rio Mayo Fall-Winter Cropping Patterns, 1994-2004

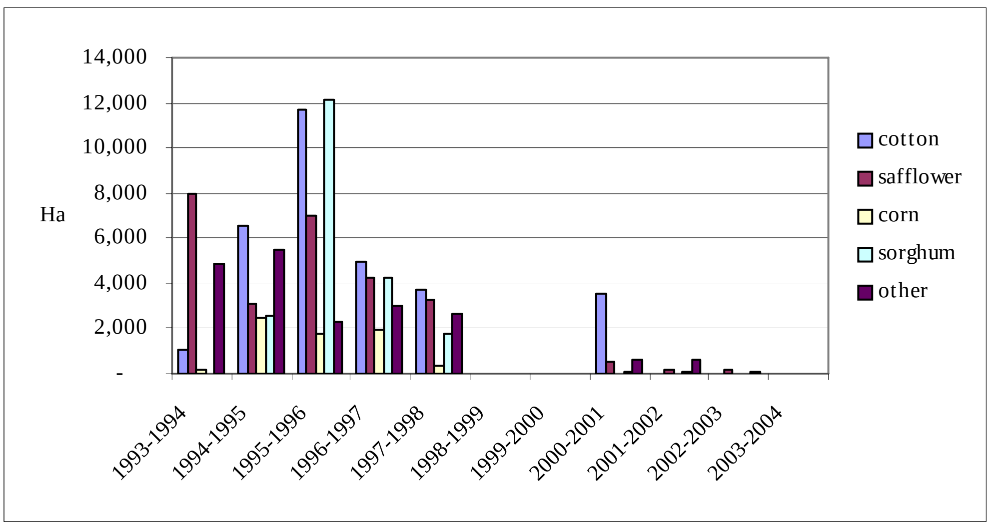

Figure 2: Rio Mayo Spring-Summer Cropping Patterns, 1994-2004

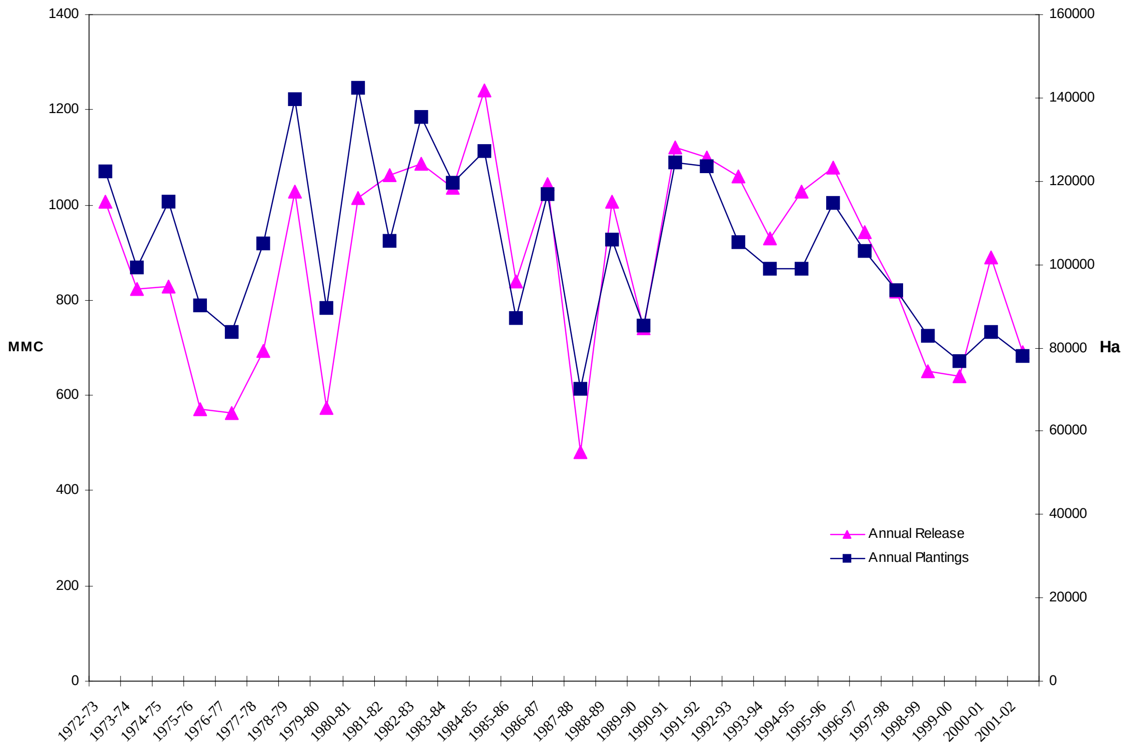

Figure 3: Annual Plantings and Annual Releases

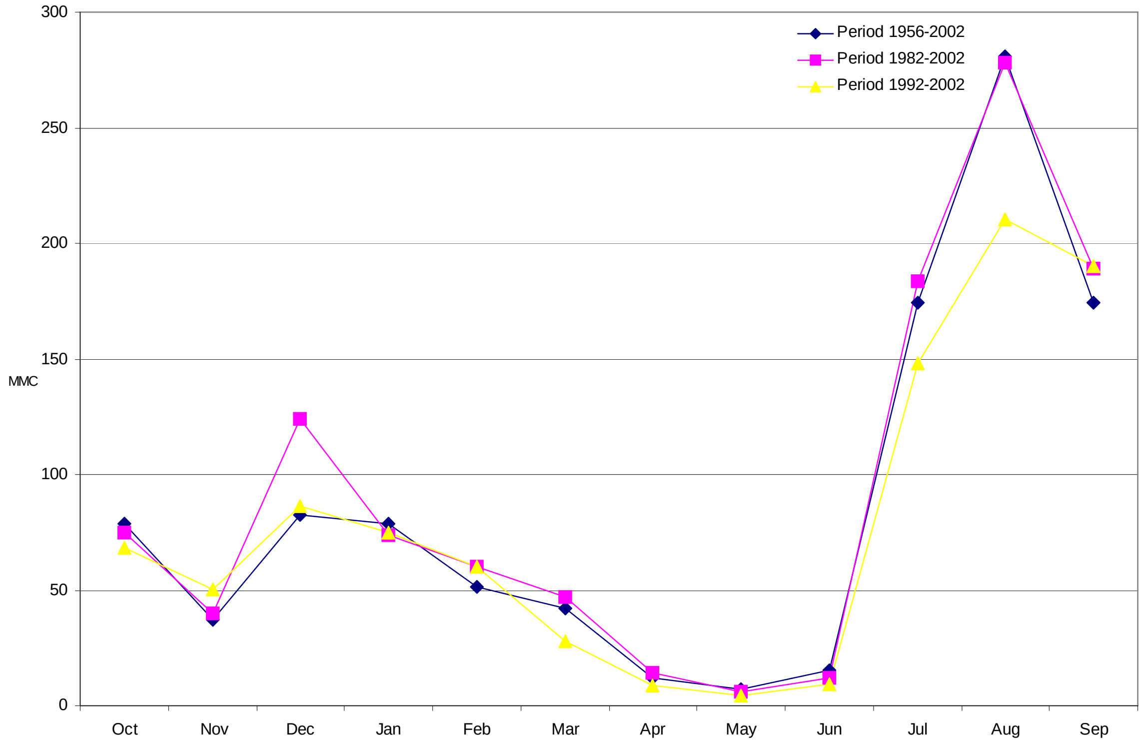

Figure 4: Rio Mayo Monthly Inflows During Three Historic Periods

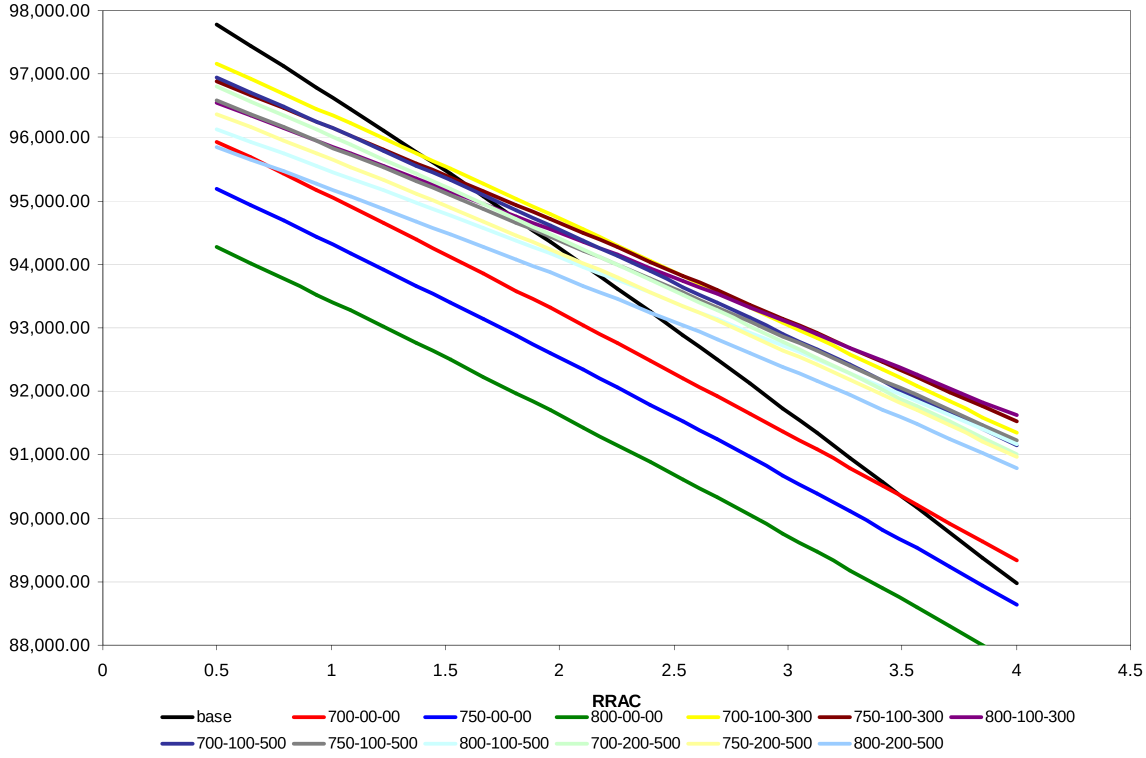

Figure 5a: SERF and CE values with a Power Utility Function for All Contracts

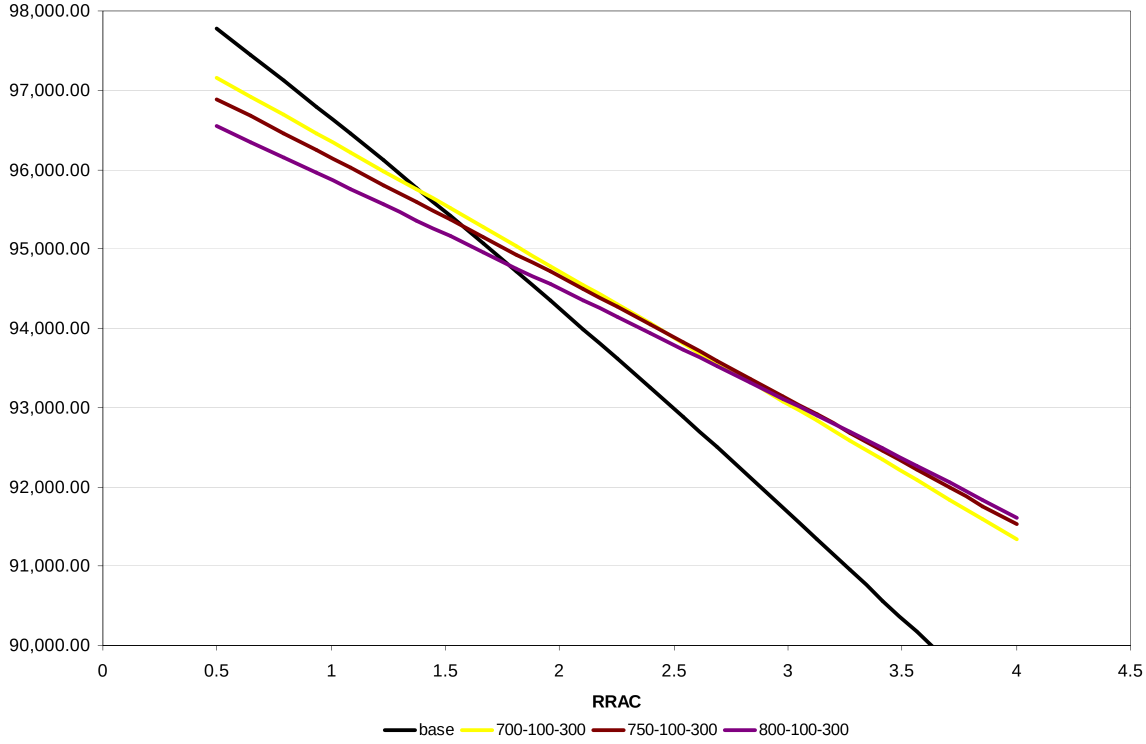

Figure 5b: SERF Efficient Set under a Power Utility Function

References

Anderson, J.R. and Dillon, J.L 1992. *Risk Analysis in Dryland Farming Systems*. Farming Systems Management Series No. 2, FAO, Rome.

Askew, A.J. 1974. "Optimum Reservoir Operating Policies and the Imposition of a Reliability Constraint." *Water Resources Research* 10(1):51-56.

Dudley, N.J. 1988a. "A Single Decision-Maker Approach to Irrigation Reservoir and Farm Management Decision Making." *Water Resources Research* 24(5):663-640.

__. 1988b. "Volume Sharing of Reservoir Water." *Water Resources Research* 24(5):641-648.

Dudley, N.J., and O.R. Burt. 1973. "Stochastic Reservoir Management and Design for Irrigation." *Water Resources Research* 9(3):507-522.

Eisel, L.M. 1972. "Chance Constrained Reservoir Model." *Water Resources Research* 8(2):339-347.

Hamilton, J.R., N.K. Whittlesey, and P. Halverson. 1989. "Interruptible Water Markets in the Pacific Northwest." *American Journal of Agricultural Economics* 71(1):63-75.

Hao, J., J. Hartell, and J.R. Skees. 2004. "Optimal Inter-Period Weighting of Cumulative Indices for Weather-Based Contingent Claims." Paper presented at AAEA annual meeting, Denver CO, 1-4 August.

Hardaker, J.B, J.W. Richardson, L. Gudbrand, and K.D. Schumann. 2004."Sochastic Efficiency Analysis with Risk Aversion Bounds: A Simplified Approach." *Australian Journal of Agricultural and Resource Economics* 48:253-270.

Iglesias, E., A. Garrido, and A. Gomez-Ramos. 2003. "Evaluation of Drought Management in Irrigated Areas." *Agricultural Economics* 29:211-229.

Kelman, J., J.R. Stedinger, L.A. Cooper, E. Hsu, and S.Q. Yuan. 1990. "Sampling Stochastic Dynamic Programming Applied to Reservoir Operations." "*Water Resources Research* 26:447-454.

Labadie, J.W. 2004. "Optimal Operation of Multireservoir Systems: State-of-the-Art Review." *Journal of Water Resources Planning and Management* 130:93-111.

Michelsen, A.M., and R.A. Young. 1993. "Optioning Agricultural Water Rights for Urban Water Supplies during Drought." *American Journal of Agricultural Economics* 75(4):1010-1020.

Naylor, R.L., W.P. Falcon., and A. Puente-Gonzalez. 2001. *Policy Reforms and Mexican Agriculture: Views from the Yaqui Valley*. CIMMYT Economics Program Paper No. 01-01. Mexico, D.F.: CIMMYT.

Richardson, J.W. 2003. *Simulation for Applied Risk Management*. Department of Agricultural Economics, Texas A&M University.

Skees, J.R. and K. Zeuli. 1999. "Using Capital Markets to Motivate Water Market Efficiency." Dept. Agr. Econ., Staff Paper No. 396, University of Kentucky, Lexington.

Skees, J.R. and A. Enkh-Amgalan. 2002. "Examining the Feasibility of Livestock Insurance in Mongolia, Volume I." Policy Research Working Paper No. WS 2886.

Skees, JR., P.Siegel, D. Larson, and P. Varangis. 2002. "Can Financial Markets be Tapped to Help Poor People Deal with Weather Risks? Volume I." Policy Research Working Paper No. WS 2812.

Stedinger, J.R., B.F. Sule, and D.P. Loucks. 1984. "Stochastic Dynamic Programming Models for Reservoir Operation Optimization." *Water Resources Research* 20:1499-1505.

Taylor, R.G., and R.A. Young. 1995. "Rural-to-Urban Water Transfers: Measuring the Direct Forgone Benefits of Irrigation Water under Uncertain Water Supplies." *Journal of Agricultural and Resource Economics* 20(2):247-262.

Turner, B., and G.M. Perry. 1997. "Agriculture to Instream Water Transfers under Uncertain Water Availability: A Case Study of the Deschutes River, Oregon." *Journal of Agricultural and Resource Economics* 22(2):208-221.

Turvey, C.G. 2001. "Weather Derivatives for Specific Event Risks in Agriculture." *Review of Agricultural Economics* 23:333-351.