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Weather Derivatives and Water Management in Developing Countries: An Application for an Irrigation District in Central Mexico

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This paper analyzes possible improvements to water allocation from introducing weather derivatives as an insurance instrument in irrigation districts with no water markets and two cropping seasons. Dry-season production depends completely on irrigation, while wet-season production depends on irrigation as a supplement to naturally occurring precipitation. Using an analytical model of water allocation and historical data from an irrigation district in Central Mexico, simulations show that weather derivatives could encourage interseasonal reallocation of water from wet to dry season, generating new Pareto-optimal water allocations that improve overall welfare among producers.

Key words: crop insurance, irrigation districts, optimal irrigation policy, water management, weather derivatives

Introduction

Extreme weather events and high variability of precipitation and temperature, commonly attributed to climate change, could aggravate competition for water to the detriment of irrigated agriculture. The latter, which depends on complex hydrological systems and inflexible infrastructure. Thus, water allocation efficiency is a major concern for water authorities that face the dual challenges of distributing a scarce resource with uncertain supply and increasing demand.

Developing countries are more dependent on agriculture and typically have incomplete water markets that prevent the development and functioning of price systems. The design and development of mechanisms that could improve water allocation efficiency is a priority. Furthermore, water authorities in regions with two crop cycles (wet and dry seasons) face additional challenges in the form of higher precipitation variability and more frequent extreme weather events, such as droughts, which could be caused by climate change.

This paper proposes incorporating weather derivatives into the water allocation decisions made by water management authorities in irrigation districts characterized by incomplete water markets and two-season crop production. In the specific case considered, dry-season production completely depends on irrigation, while wet-season production depends on irrigation as a supplement to naturally occurring precipitation. At the beginning of the hydrological year, the water authority allocates water across both crop seasons in response to the known producers' water demand. Producers lack the ability to store water on site or reallocate it across seasons and thus completely depend on the decisions of the water authority.

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Weather derivatives are contingent claim contracts that provide payoffs conditional on the occurrence or nonoccurrence of a specific weather event (in this case, lack of precipitation). They essentially serve as a substitute for water and allow the authority to improve water allocation decisions. Weather derivatives assure the wet-season producers of either sufficient water supply to generate normal crop yields or monetary reimbursement during droughts. This, in turn, allows the water authority to reallocate water from wet-season to dry-season production.

The problem of efficient water allocation between wet and dry seasons under uncertainty has been analyzed in the literature (e.g., Vedula and Mujumdar, 1992; Prasad, Umamahesh, and Viswanath, 2006). The potential use of weather derivatives as insurance instruments for agricultural production has also been discussed before (e.g., Barnett, Barrett, and Skees, 2008; Vedenov and Barnett, 2004; Martin, Barnett, and Coble, 2001). However, to the best of our knowledge, the present paper is the first attempt to directly incorporate the use of weather derivatives into water allocation decisions for agricultural production. We build on the dynamic optimal resource allocation model discussed by Miranda and Fackler (2002) and analyze how the optimal allocations are affected by the availability of weather derivatives.

The model is applied to the case of Alto Rio Lerma Irrigation District (ARLID) in Central Mexico. ARLID is representative of operations in a typical irrigation district in a region characterized by two cropping seasons. The district possesses a minimal organizational structure and operates under conditions comparable to other irrigation districts across Latin America. Thus, the results of our analysis are extendable to a wide range of regions with two cropping seasons, including the Argentinian Pampas, the Lesser Antilles, Central America, Colombia, and the Amazonian basins of the Andean countries where supplementary irrigation is required during the wet season.

Literature Review

The economic literature has extensively documented water scarcity and increasing demands for competing uses such as agricultural, urban, industrial, and mining applications (Loucks et al., 2005; Milly et al., 2008; Brown, 2010; Olmstead, 2014; Organisation for Economic Co-operation and Development, 2015). In this context, allocation arrangements consisting of a combination of policies, mechanisms, and formal and informal appointments (entitlements, licenses, permits, and rights) determine how a resource pool is distributed across users. Thus, allocation arrangements have a relevant role in guiding policies to cope with the risk of water shortage and climate variability.

In theory, various water allocation schemes may produce efficient distributions through market-based mechanisms that manage water demand from low- to high-valued niches using price schemes, auctions, or property rights (Dinar, Pochat, and Albiac-Murillo, 2015). However, no market mechanisms are usually available in developing countries, and weak water policies such as underpricing may prevent the implementation of feasible schemes to attain more efficient water allocations under uncertainty (Organisation for Economic Co-operation and Development, 2015).

Agriculture demands about 70% of available freshwater worldwide (Turner et al., 2004). Agricultural systems are incorporated into watersheds or river basins that usually require complex planning and management of water resources (Loucks et al., 2005). In general, allocation arrangements in irrigation districts rely on reservoir release rules executed under uncertain conditions of storage, runoffs, and inflows. However, water allocation policies are typically based on institutional arrangements with highly inflexible rules and almost no capacity to adapt to resource scarcity pressure.

In the economic literature, water allocation policies have been largely analyzed using one of three approaches (Yeh, 1985; Singh et al., 2016). Linear programming has been extensively used to identify and evaluate alternative plans, designs, and management policies (Yaron and Dinar, 1982; Moradi-Jalal et al., 2007). However, this approach has a limited capacity to evaluate complex systems and the objectives of all stakeholders (Singh et al., 2016). Nonlinear programming is a more complete approach, but it has limited ability to incorporate stochasticity and is characterized by the slow convergence rate of the available algorithms (e.g., Shang and Mao, 2006). Dynamic programming is the most comprehensive approach for irrigation planning and management due to its capacity to model the sequential decision-making process, incorporate nonlinearity, and allow for stochasticity in hydrological processes (e.g., Ben Alaya et al., 2003; Prasad, Umamahesh, and Viswanath, 2006; Singh et al., 2016).

While the idea of using weather derivatives as an insurance mechanism for agricultural production is not entirely new (e.g., Varangis et al., 2001; Mahul, 2001; Martin, Barnett, and Coble, 2001; Miranda and Vedenov, 2001; Turvey, 2001; Dischel, 2002; Vedenov and Barnett, 2004), the literature that focuses on applying these instruments in water allocation problems is somewhat limited (e.g., Leiva and Skees, 2008; Zeuli and Skees, 2005; Brown and Carriquiry, 2007). Furthermore, most of these papers are mainly concerned with the benefits to the decision-makers rather than the agricultural producers who are directly affected by the decisions. For example, Zeuli and Skees (2005) design a rainfall index contract to correct inefficiencies produced by water management systems during droughts. The authors analyze the effectiveness of this contract from the standpoint of the water management authority and show that index insurance creates incentives for the authority to more accurately estimate the availability of water supply and demand. But they do not consider the changes of farmers' welfare given the reallocation of water.

Maestro, Bielza, and Garrido (2016) design hydrological drought index insurance based on water stocks for irrigation districts. They assess the hedging effectiveness of the instrument and show that the proposed instrument is able to reduce farmers' vulnerability to water shortages in the irrigation district. Nevertheless, they do not analyze farmers' welfare.

Brown and Carriquiry (2007) propose an index insurance based on reservoir inflows to cover the financial needs of a water supplier during persistent droughts. They suggest that the availability of the instrument for agricultural water users could make them better off. However, the proposed mechanism works only when the water market is competitive and some farmers can forego their full allocation in some years.

Leiva and Skees (2008) design a financial instrument based on river flow accumulation as a market-based alternative to managing water supply risk. Using the Rio Mayo irrigation system in northwestern Mexico as a study case, the authors develop a stochastic model that incorporates water release rules and response functions that capture the physical relationship between irrigation water, conveyance efficiency, and the size of the irrigated area. The authors conclude that insurance is a feasible option from both the demand and supply sides, and it could be a cost-effective way for mitigating water supply risk.

Our paper expands on the existing literature and the approach taken by Leiva and Skees (2008) in several ways. First, producers' well-being is explicitly incorporated into the water allocation problem. Second, while weather derivatives are modeled as risk-reduction mechanisms as in previous studies, we show that they can be interpreted as a substitute for water. Lastly, we model water allocation decisions in a two-season production setting, which is common in many Latin American countries.

Water Allocation Model

Our model characterizes a stylized irrigation district—an administrative entity that is typically responsible for allocating water to users who have nontransferable water rights established by law and linked to a particular piece of land property. The irrigation district typically includes several irrigation modules, each of which receives its own allocation. However, without loss of generality, we focus our analysis on a single module in the district.

Following the general framework outlined in Miranda and Fackler (2002), we consider a water authority that allocates reservoir water for irrigation purposes between two cropping seasons—dry and wet. We assume that a single representative farmer grows two different crops on a given plot of land—each crop grown in its respective season—and receives seasonal water allotments from the water management authority. The crops grown represent the best use of land given their water requirements and prevailing weather conditions.[1] The dry-season crop depends exclusively on irrigation, while the wet-season crop depends on initial irrigation to ensure germination and on random in situ rainfall thereafter.

Each year, at a predetermined date, the water authority evaluates the availability of water for the module versus the farmer's water demands and makes decisions about water allocation for both seasons. We assume that the farmer lacks on-site water storage infrastructure and cannot reallocate received irrigation water across seasons, which is frequently the case in many developing countries.

Without loss of generality, these assumptions simplify our problem to an intertemporal allocation of a given volume of water, which allows us to concentrate on improvements in water use efficiency due to the introduction of weather derivatives.

Baseline Model

Let s_t be the amount of water available at the beginning of year t and allocated to a given module within the district. This water is held in an upstream reservoir, and the water authority decides to release amount w_t^{dry} of water during the dry season and w_t^{wet} during the wet season. The total allocation cannot exceed the available supply (i.e., $0 \leq w_t^{dry} + w_t^{wet} \leq s_t$. During the rainy season of year t, the reservoir is replenished by random inflows ε_t, which can be thought of as a combination of runoff in the basin entering the reservoir as well as rainfall falling directly above the reservoir. Thus, at the beginning of period $t+1$, the available water for the module is represented by the controlled Markov process:

$$s_{t+1} = s_t - w_t^{dry} - w_t^{wet} + \alpha\varepsilon_{t+1}, \tag{1}$$

where α is a proportion of the inflow water allocated to the module.

We assume that the representative farmer is risk averse with preferences characterized by a utility function $u(\cdot)$ defined over the profit π, which depends on the total amount of water received for crop production (both from the reservoir and random in situ rainfall x_t). In particular, we define per acre profit in season $i \in \{dry, wet\}$ of period t as

$$\pi_t^i = P_t^i - P_w w_t^i - c_t^i, \tag{2}$$

where y_t^i is the yield of crop grown in season i, P_t^i is the corresponding nonrandom output price,[2] P_w is the price of irrigation water assumed to be constant over time,[3] and c_t^i represents the total cost of all other inputs (i.e., seeds, fertilizer, etc.) besides water.

We assume that the farmer uses a divisible technology characterized by a quadratic production function. For the purposes of this analysis, we assume that for each season i the crop production functions y^i depend explicitly only on the total amount of water received either from irrigation or from rainfall. Hence, we consider both sources of water as perfect substitutes. Specifically, the production functions are

$$y^{dry} = a_0 + a_1 w^{dry} + a_2 (w^{dry})^2, \tag{3}$$

$$y^{wet} = b_0 + b_1 (w^{wet} + x) + b_2 (w^{wet} + x)^2, \tag{4}$$

[1] This assumption is a fairly realistic reflection of growing practices in many Latin American countries, where a combination of soil fertility, weather patterns, economic conditions, and cultural practices limits farmers' ability to diversify their risk via crop rotation or adjustments in land allocation.

[2] The farmer is assumed to be small enough so that input and output prices are not affected by the farmer's decisions.

[3] If the price of irrigation water were not constant, it would be a decision variable for the water authority. Thus, the dynamic optimal allocation would depend on the optimal path of the water price established by the authority. Analysis of such a model can be carried out within the presented framework but is beyond the scope of this paper.

where x is the random rainfall received within the module. The farmer's demand function for water in any given period t can be then derived from the expected utility maximization condition:

$$\max_{w^{dry},w^{wet}} E_x \left[u \left(\sum_{i=dry,wet} \pi_t^i(w_t^i) \right) \right], \tag{5}$$

where π_t^i is defined by equations (2)–(4), and the expectation is taken with respect to a degenerate distribution in the case of $i = dry$. Since we are primarily interested in the marginal effects of water on crop yields, we assume that the farmer has already decided on the amount of other inputs.[4]

The solution to equation (5) is the irrigation water demand functions $w_t^{dry}(P_t^{dry}, P_w)$ and $w_t^{wet}(P_t^{wet}, P_w)$, which encompass all of the farmer's private information on technologies and preferences driving demands. The inverse demand function would be $P_w(w_t^i, P_t^i)$.

We assume that the water authority knows the farmer's water demand functions and therefore its problem is to allocate water in each season over time so as to maximize farmers' surpluses. Namely, we solve[5]

$$\max_{w_t^{dry};w_t^{wet}} E_0 \sum_{t=0}^{\infty} \delta^t \left[\int_0^{w_t^{dry}} [P_w(\tilde{w}, P_t^{dry}) - P_w] d\tilde{w} + \int_0^{w_t^{wet}} [P_w(\tilde{w}, P_t^{wet}) - P_w] d\tilde{w} \right], \tag{6}$$

subject to the state transition equation (1), where δ is the discount factor. The solution for this problem is the optimal water allocation strategies $(\tilde{w}^{dry}, \tilde{w}_t^{wet})$ based on the farmer's water demand functions, which should be implemented in every state at each point in time in order to maximize the total expected discounted value of the farmer's utility over an infinite lifetime.

This is a discrete time, discrete state Markov decision problem in which the farm's decision problem is incorporated into the authority's problem.[6] It can be analyzed using dynamic programming methods based on Bellman's principle of optimality (Miranda and Fackler, 2002).

This principle implies that the problem in equation (6) can be rewritten as a condition that the value function $V(s)$, which specifies the maximum attainable sum of current and expected future rewards given that the current reservoir level is s, satisfies the Bellman equation

$$\begin{aligned} V(s) \quad = \quad & \max_{w^{dry};w^{wet}} \left\{ \int_0^{w^{dry}} [P_w(\tilde{w}, P_t^{dry}) - P_w] d\tilde{w} \right. \\ & \left. + E \int_0^{w^{wet}} [P_w(\tilde{w}, P_t^{wet}) - P_w] d\tilde{w} + \delta E V(s') \right\}, \end{aligned} \tag{7}$$

where $s' = s - w^{dry} - w^{wet} + \alpha\varepsilon'$ as per equation (1). The Bellman equation reflects a trade-off in allocating water between two different seasons of the same year as well as a trade-off between total allocation in current and subsequent years.

Incorporating Weather Derivatives

Weather derivatives are contingent claim contracts written on realization of an index such as cumulative rainfall over a defined period, heating degree days, or cooling degree days (Brockett et al., 2009). Most contracts are structured as put (call) options that pay an indemnity if a specific weather variable falls below (rises above) a pre-specified level (e.g., Martin, Barnett, and Coble, 2001).

[4] The constant terms in equations (3) and (4) may represent conventional inputs (e.g., labor and capital) evaluated at the "optimal" levels. The assumption of deterministic production functions is not limiting, since any random shocks independent of uncertainty in water availability do not affect the optimal water allocation decisions.

[5] Non-water production costs c_t^i were incorporated into the numerical model. However, the costs would not affect the solution to this problem but would affect the magnitude of the value function.

[6] Without loss of generality, this problem can also be treated as a discrete time, continuous state Markov decision model.

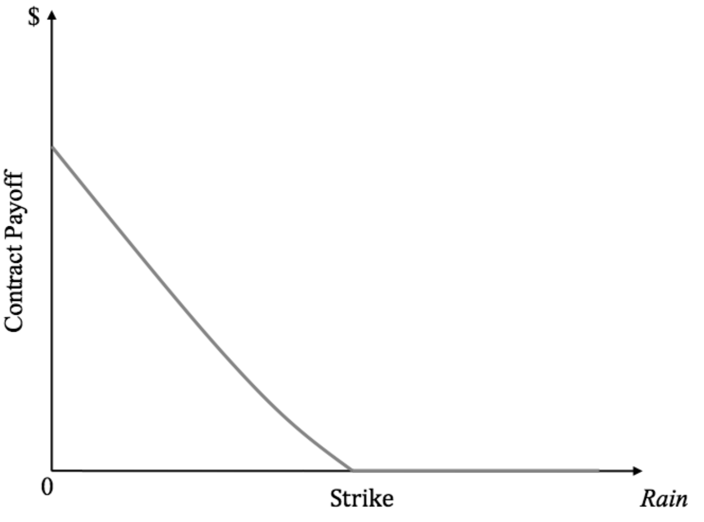

Figure 1. Payoff Structure of the Weather Derivatives Contract

For the purposes of this paper, we use a contract structure based on Vedenov and Barnett (2004). Namely, we define the contract as a put option without imposing any limits on contract payoff (the "fully proportional" contract described by Vedenov and Barnett, 2004). Such a contract pays nothing as long as the index is within the acceptable range and pays a proportionally higher indemnity whenever the index falls below a specified strike.

The cumulative rainfall x_t received within the module is used as the index, and the strike is set equal to expected rainfall $E(x)$ multiplied by the coverage level θ:

(8) $$strike = \theta E(x).$$

The profit from growing the wet-season crop with no irrigation water allocated and natural rainfall equal to the strike,

(9) $$\overline{\pi} = P_{wet}[b_0 + b_1 strike + b_2 strike^2],$$

is then used to set the level of protection provided, so that for a given amount w^{wet} of water allocated, the contract pays an indemnity according to the schedule

(10) $$I(x|\theta, w^{wet}) = \begin{cases} \overline{\pi} - \pi(w^{wet}) & \text{if } x \leq strike \\ 0 & \text{if } x > strike \end{cases}$$

Figure 1 illustrates the indemnity function in equation (10), which depends on the realization of rainfall x given coverage level θ and the amount of water w^{wet} allocated for the wet-season crop. The farmer pays the insurance premium, which (without loss of generality) we assume to be actuarially fair and set equal to the expected payoff of the contract:[7]

(11) $$P(\theta, w^{wet}) = E_x[I(x|\theta, w^{wet})].$$

Figure 2 shows total profits of the wet-season crop with and without the weather derivative, with the vertical distance between both functions representing the indemnity payment.

[7] Premium load can be incorporated into the model as a multiplier $(1 + \lambda)$ in front of the expectation in equation (11). However, this would not affect the solution methodology or qualitatively change the results.

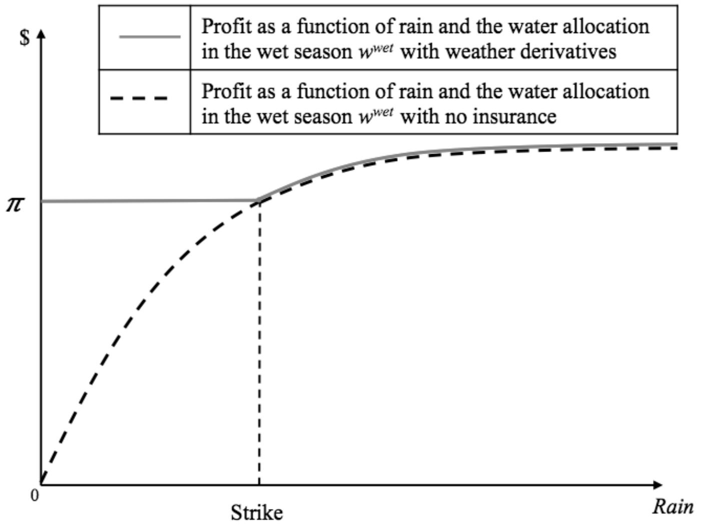

Figure 2. The Profit Functions π of the Wet-Season Farmers With and Without Weather Derivatives

The insurance payment modifies the farmer's profit in the wet season, but otherwise the water allocation model in equation (6) remains the same. The optimal water allocation policies $\tilde{w}^{dry}(s)$ and $\tilde{w}^{wet}(s)$ in the presence of insurance can be again calculated by solving the Bellman equation (7) with the appropriate modifications:

$$\begin{aligned} V(s) \quad = \quad & \max_{w^{dry};w^{wet}} \left\{ \int_0^{w^{dry}} [P_w(\tilde{w}, P^{dry}) - P_w] d\tilde{w} + E\bigg(I(x|\theta, w^{wet}) - P(\theta, w^{wet}) \right. \\ & \left. + \int_0^{w^{wet}} [P_w(\tilde{w}, P^{wet}) - P_w] d\tilde{w} \bigg) + \delta EV(s') \right\}. \end{aligned} \tag{12}$$

Numerical Solution of Bellman Equation

Generally, the Bellman equation (7) does not have a closed-form solution but can be solved numerically. In order to do so, we assume that the reservoir level s takes only discrete value in the state-space S, which enumerates all the states attainable by the system. Similarly, the action space W enumerates all possible (discrete) actions or water allocations w^{dry} and w^{wet} that may be taken by the water authority. Both spaces are assumed to be finite, and the water allocation decisions should satisfy the conditions

$$w^{dry} \leq s, \tag{13}$$

$$w^{wet} \leq s - w^{dry}. \tag{14}$$

The probability distributions of rainfall p_x in the module and the probability distributions of annual inflow p_ε to the reservoir are also discretized over the respective domains. Assuming the infinite horizon, the Bellman equation (7) can be then expressed as a functional fixed-point equation:

$$
\begin{aligned}
V(s) \; = \; & \max_{w^{dry};w^{wet}} \left\{ \int_0^{w_t^{dry}} \left[P_w(\tilde{w}, P_t^{dry}) - P_w \right] d\tilde{w} + \sum_{x \in X} p_x \int_0^{w_t^{wet}} \left[P_w(\tilde{w}, P_t^{wet}) - P_w \right] d\tilde{w} \right. \\
& \left. + \; \delta \sum_{\varepsilon \in H} p_\varepsilon V \left(s - w^{dry} - w^{wet} + \alpha\varepsilon \right) \right\}, \qquad (15)
\end{aligned}
$$

where the expectations in equation (7) are replaced by their discrete forms. If the discount factor δ is lower than one and the utility functions for both wet and dry seasons are bounded, then, by the Contraction Mapping Theorem, this Bellman equation possesses a unique solution.

The policy iteration algorithm (Miranda and Fackler, 2002) can be used to solve equation (15) numerically. The solution steps involve making a guess as to the initial value of V, solving the optimization problem in equation (15) to find the optimal w^{dry} and w^{wet} for the current value of V, and updating V. The solution is obtained when convergence is achieved. Since the total number of states is finite, the total number of admissible policies is also finite. Therefore, the policy iteration algorithm will terminate finitely after many iterations with an exact optimal solution. The model was implemented in MATLAB using the CompEcon toolbox developed by Miranda and Fackler (2002).

Dynamic Simulation Analysis

The optimal policy functions w^{dry} and w^{wet} provide rules about how the water authority should allocate water given the farmer's water demand function and the reservoir level. The dynamics of the model can be then studied using the dynamic path and the steady-state analysis.

The dynamic path analysis evaluates the expected path followed by both the reservoir level and the optimal irrigation policy over time starting from an initial value of the reservoir level. The expectation is taken by averaging a large number of paths generated by the Monte Carlo method based on the probability transition matrix, the optimal policy, and the vector of initial reservoir levels. The steady-state distribution is obtained as the limit of the transition probability matrices $\boldsymbol{Q}_t = PR(\varepsilon_t = \varepsilon)$ as $t \to \infty$.

Parameterization of Preferences

We assume that the representative farmer's preferences are described by the constant relative risk aversion (CRRA) utility function

$$u(\pi, \gamma) = \frac{\pi^{1-\gamma}}{1-\gamma'}, \qquad (16)$$

where γ is the risk aversion parameter. Financial and economics literature suggest the use of CRRA to represent the agent's preferences (Cairns, Blake, and Dowd, 2006). Brandt, Santa-Clara, and Valkanov (2009) point out that CRRA possesses desirable properties—such as double differentiability and continuity—that increase the efficiency of numerical optimization algorithms while incorporating preferences toward higher-order moments in a simpler way.

Application: Water Allocation Decisions in the ARLID in Guanajuato, Mexico

In order to analyze the effect of weather derivatives on water allocation policy, we consider the Alto Rio Lerma Irrigation District (ARLID) in the Lerma-Chapala river basin system in Guanajuato, which by 2030 is expected to experience high water stress and more frequent instances of heavy rain followed by prolonged droughts (CONAGUA, 2010).

The National Water Commission (CONAGUA by its Spanish acronym) is a technical and consultative agency that manages water resources in Mexico through thirteen river basin organizations. By the second week in September of each year, CONAGUA determines water supply in the basin based on calculated runoff generated from the previous November through August and forecasted rainfall for September and October (Comision Nacional del Agua (CONAGUA), 2010). Once the annual volume of restitution run-off is calculated, CONAGUA provides water needed to carry out planting activities in irrigation districts. CONAGUA also determines fees based on the allocated volume of water and receives part of these fees as a recuperation payment (Kloezen and Garces-Restrepo, 1998).

ARLID has an average temperature of 18–20°C, favorable soils, and an average annual precipitation of 670mm during the wet season (May through October) and 80mm during the dry season (November through April). ARLID's farmers competitively produce a wide range of crops including grains, perennials, and vegetables for export (Comision Nacional del Agua (CONAGUA), 2010).

For the purposes of operation and management, ARLID is organized into eleven modules, each of which is managed independently. All distributional operations are based on a water rights system that awards property rights and assigns detailed roles and responsibilities to modules.[8] Each module is entitled to a proportional share of water available for the irrigation district. The modules are also in charge of the final water allocation for its users and collecting fees from them.

A limited liability company (LLC) operates, manages, conserves, and maintains the irrigation network of ARLID—which includes primary canals, secondary canals, and drainage—and coordinates and monitors modules. The LLC plans on a weekly basis the delivery of water resources to the modules and checks ditch-tender reports at each module. Due to a growing water shortage and low average efficiency in transmission (65%), ARLID provides irrigation water for only 70% of the registered physical surface, where the water property rights are concentrated.

ARLID's irrigation plans and the first crop season start in early November, after the hydrological cycle of the basin begins. The dry season crop (November to April) is a priority because it depends completely on irrigation. Production in the wet season (May to October) depends on both rainfall and irrigation.

Water Allocation in ARLID

The volume of water that each module receives is based on an irrigation plan, which is the result of negotiations between the CONAGUA, the LLC, and the modules (Kloezen and Garces-Restrepo, 1998). The water demand is projected based on the intended planting estimates that LLC submits to CONAGUA, which makes up the difference between water demand and supply in this period. CONAGUA estimates the difference based on the amount of water available at the end of the previous period.

For the purposes of this paper, we focus on the module Valle de Santiago (Valle), located in the center of ARLID. This module is the third largest in terms of irrigated area and was selected because of its high efficiency rate in conduction (92%). This efficiency reflects the conservation state of the infrastructure, its operational feasibility, and (indirectly) a well-organized ownership structure, all of which can be useful for the establishment and functioning of an insurance scheme. Farmers in the module primarily grow barley during the dry season and sorghum during the wet one.

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[8] The water rights system requires the concessionaire to pay for the volume of extracted water. The payment is set in relation to shortages in every region of the country and with different rates for every use. Industry and services pay more than urban users, while water for agriculture and farm-related activities is free. Thus, the fees paid by water users are related to the cost of operation fee for the irrigation district infrastructure and for the use of the main infrastructure (dams, channels, etc.) that CONAGUA operates.

Table 1. Descriptive Statistics of Crop Yields and Water Allocation in Module Valle

	Mean	Std. Dev.	CV	Min	Max	Range of Data
Yield (tons/ha)						
Barley	5.065	0.871	0.172	3.380	6.500	1985–2011
Sorghum	6.662	1.285	0.193	4.408	10.650	1985–2005
Allocated water (TCM/ha)						
Barley	5.776	0.347	0.060	4.663	6.201	1989–2011
Sorghum	2.920	0.687	0.235	2.081	5.003	1989–2011

Notes: CV stands for coefficient of variation. TCM/ha stands for thousands of cubic meters per hectare. Barley is the dry-season crop; sorghum is the wet-season crop.

Table 2. Estimates of Yield Trend Models

Coefficients	Barley Yield (tons/ha)	Sorghum Yield (tons/ha)
a_0	0.375	1.018
	(0.004)	(0.097)
b_0	0.0666	0.0661
	(0.000)	(0.138)
b_1	0.199	0.167
	(0.097)	(0.033)
c_1	1991	1994.5
	(0.000)	(0.000)
b_2	−0.0592	−0.149
	(0.000)	(0.052)
c_2	2009	1999.5
	(0.000)	(0.000)
N	22	17
Adj. R-square	0.301	0.209

Notes: Numbers in parentheses are p-values.

Yield Data

Historical module-level yield series for sorghum and barley were collected from the Sistema de Información Agropecuaria y Pesquera (2013). This dataset for Valle is available from 1985 to 2011. Historical water allocations for both crops were obtained from Comision Nacional del Agua (CONAGUA) (2010). Table 1 displays the range of available data and descriptive statistics for both crop yields and water allocations. The average yields during the analyzed period were 5.06 tons/ha for barley and 6.66 tons/ha for sorghum. Since barley is grown during the dry season, barley farmers have historically received higher water allocations than sorghum farmers (5.77 TCM/ha versus 2.92 TCM/ha).[9]

The KPPS test, the Dickey-Fuller test, and the Phillip-Perron test were performed to determine whether yield and water allocation series have trends. All tests agree that yield series are trend stationary and historical water allocations are stationary. New barley and sorghum varieties have been introduced in Valle de Santiago over time, which made crop yields incomparable across years. To address this problem, yields were detrended using a two-knot piecewise linear trend model (Vedenov, Epperson, and Barnett, 2006):

$$y_t = a_0 + b_0(t - t_0) + b_1\delta_1(t - c_1) + b_2\delta_2(t - c_2) + u_t, \tag{17}$$

where y_t is the yield recorded in year t, $t_0 = 1984$ is the "zero" year of yield observations, c_1 and c_2 are regime-switching points (years when the slope of trend function changed), and $\delta_i, i = 1,2$ are dummy variables equal to 1 for $t \geq c_i$ and 0 otherwise. The estimation results are reported in table 2.

[9] TCM/ha is 1,000 cubic meters per hectare and is equivalent to 100 mm of precipitation.

Table 3. Descriptive Statistics of Cumulative Rainfall in Valle (Module) and Dam Solis (Reservoir)

	Rainfall in Valle	Rainfall in Solis
Mean	117.74	726.06
Std. Dev.	56.28	195.76
CV	0.48	0.27
Minimum	10.88	197.90
Maximum	250.50	1133.50
Skewness	0.38	−0.70
Kurtosis	2.66	3.77
α - shape	3.55	10.25
β - scale	33.20	70.86
Period of time	1943–2010	1962–2011

Notes: Mean and standard deviation are in millimeters. CV stands for coefficient of variation.

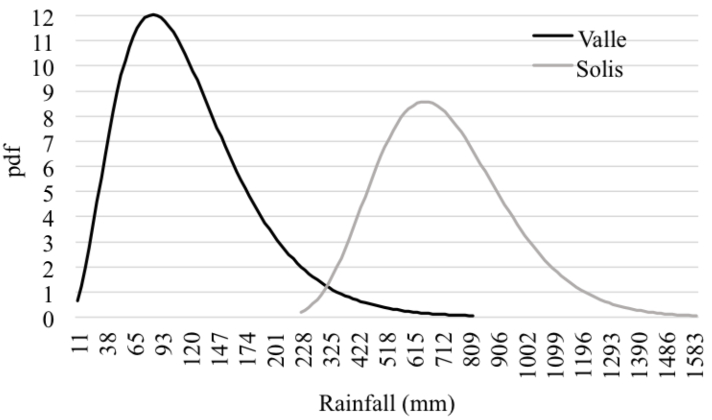

Figure 3. Fitted Gamma Distribution for Cumulative Rainfall in Valle (Module) and Solis (Reservoir)

Rainfall Data

We collected daily precipitation data from the Servicio Meteorológico Nacional (2011) for two weather stations corresponding to module Valle and dam Solis (the reservoir location).

Cumulative rainfall at Valle between April and June was used to reflect in situ precipitation received during the wet season (x in equation 4). The cumulative rainfall at dam Solis from November of year t through October $t+1$ was used as a proxy for reservoir inflows (ε in equation 1). Table 3 reports descriptive statistics of both cumulative rainfall variables. Unit root tests suggest that all series are stationary. For the purposes of analysis, gamma distributions were fitted to both cumulative rainfall series. The estimated parameters are also reported in table 3. The fitted distributions are shown in figure 3.

Parameterization

Table 4 summarizes parameter values used in the analysis. For the purposes of numerical solution, the reservoir capacity $\overline{S}$ was set to 10 TCM/ha. This value does not necessarily represent the actual capacity of the reservoir associated with module Valle, but it allows us to define the space of state variables. The domain of state decision variables was discretized using 101 nodes.

Table 4. Parameters Used in the Dynamic Model of Water Allocation

Parameter	Value	Units/Description
$\overline{S}$	10	TCM/ha (maximum reservoir level)
α	0.11	Share of rainwater attributable to Valle
γ	1 to 3	Risk aversion coefficient
θ	100	% (coverage level)
r	5	% (interest rate)
δ	0.952	Discount factor equal to $1/(1+r)$
P_{dry}	3,900	Pesos/tons (price of barley)
P_{wet}	4,500	Pesos/tons (price of sorghum)
P_w	160	Pesos/TCM (price of water)
c_t^{dry}	11,000	Pesos/hectare (cost of other inputs for barley)
c_t^{wet}	8,500	Pesos/hectare (cost of other inputs for sorghum)

Table 5. Estimated Crop Production Functions

Variables	Barley	Sorghum
Irrigation Water	0.4353	
	(0.016)	
Irrigation Water Squared	−0.000377	
	(0.066)	
Rainfall + Irrigation Water		0.0983
		(0.072)
Rainfall + Irrigation Water Squared		−0.0000949
		(0.072)
Constant	−119.18	−16.8
	(0.021)	(0.188)
N	19	11
R-squared	0.312	0.361
Adj. R-squared	0.226	0.201

Notes: Numbers in parentheses are p-values.

The proportion of rainfall water attributable to module Valle α was set to 0.11, which corresponds to the water right assigned by ARLID to module Valle. The risk aversion parameter was set to 2 with values between 1 to 3 used for sensitivity analysis (Myers, 1989). The coverage level θ and the interest rate r were set to 100% and 5%, respectively. The discount factor δ was then calculated as $1/(1+r)$.

Crop and water prices were set equal to their 2010 levels (the latest data available) and expressed in pesos per tons. The total costs of all other inputs were set equal to 8,500 pesos/ha for sorghum and 11,000 pesos/ha for barley.

The discretized distributions of cumulative rainfall used to compute expectations in equation (15) were constructed from the fitted gamma distributions using 101 node gamma quadratures (Miranda and Fackler, 2002).

Parameters of the production functions in equations (3) and (4) were estimated from the collected data (table 5). Detrended barley yields were regressed on water allocation for the dry season. Detrended sorghum yields were regressed on water allocated for the wet season plus cumulative precipitation received from April through June. All estimated parameters were statistically significant at the 10% level, except for the constant term in the sorghum production function.

The optimal water allocation policies were calculated on a grid of 101 nodes over the space state, which allows for accuracy of 0.1TCM/ha to determine the optimal policy. The dynamics of

Table 6. Optimal Allocation Strategies With and Without Weather Derivatives (WD)

	Without Weather Derivatives	With Weather Derivatives
Steady-state allocation level TCM/ha	1.11	1.21
% water allocated to dry season	75	100
% water allocated to wet season	25	0
% change in expected utility from dry-season crop due to WD		30.6
% change in expected utility from wet-season crop due to WD		5.2
% change in value function due to WD		12.4
% change in total profit due to WD		17.2
% change in standard deviation of profit due to WD		21.6

the water level in the reservoir were analyzed by simulating 10,000 state variable evolution paths over a fifty-year horizon.

Results and Sensitivity Analysis

Table 6 shows the optimal water allocation policy for the baseline case (all parameters as per table 4) with and without weather derivatives. The allocations for wet and dry seasons are reported as a percentage of the optimal allocation at the steady state.

The availability of weather derivatives leads to higher total amount of water allocated by the water authority but also to a shift in allocation from wet to dry season to the point that the farmer receives no water at all during the wet season. This result suggests that weather derivatives indeed serve as a substitute for irrigation water and, instead of receiving water, the producer relies on the payments provided by weather derivatives to supplement any loss of income due to insufficient precipitation. Furthermore, the water authority now can allocate higher amounts of water to dry season production rather than holding back a certain amount to ensure sufficient availability for future years in case of shortfall in the reservoir inflows. As a consequence, the expected utility of production increases in both seasons, as does the overall welfare as measured by the value function.

In order to analyze the sensitivity of our results to assumptions made about the model parameters, the optimal policies were calculated for several scenarios and compared with the baseline case.

Table 7 reports the optimal allocation policies for different risk aversion parameters as well as for different ratios between the prices of wet- and dry-season crops (sorghum and barley, respectively). Intuitively, higher (lower) risk aversion means that the farmer would be less (more) willing to rely on random rainfall during the wet season instead of guaranteed water allocation. On the other hand, increase (decrease) in the relative price of the wet-season crop would increase (decrease) the farmer's demand for water during the wet season relative to the dry season.

As expected, increasing risk aversion leads to higher water allocation to wet-season production. The farmer's utility from both crops as well as overall welfare also increase due to higher total allocation. Changes in the relative prices of wet-season and dry-season crops do not seem to affect water allocation across seasons (although they obviously lead to changes in the expected utility of crop production and overall welfare). This somewhat counterintuitive result can be explained by the fact that weather derivatives provide adequate substitute for irrigation water, and therefore the water authority does not find it optimal to shift water allocation.

Table 8 reports the changes in optimal allocation policies with weather derivatives due to changes in parameters of rainfall distributions at the module and at the reservoir site. The baseline case corresponds to the shape parameters of gamma distributions estimated based on the historical data (table 4). In particular, a decrease in the shape parameter shifts the rainfall distribution to the left and corresponds to lower levels of precipitation either at the module itself or at the reservoir site. Lower in situ rainfall leads to increasing proportion of water allocated to wet season production.

Table 7. Sensitivity of Optimal Allocation Policies with Weather Derivatives (WD) to Relative Risk Aversion Parameter and Changes in Crop Price Ratio

	Baseline Case ($\gamma = 2.0$, $P_{wet}/P_{dry} = 1.15$)	**$\gamma = 2.5$**	**$\gamma = 1.5$**	**25% Decrease in P_{wet}/P_{dry}**	**25% Increase in P_{wet}/P_{dry}**
Steady-state allocation level TCM/ha	1.21	1.24	1.18	1.23	1.22
% water allocated to dry season	100.0	87.5	100.0	100.0	100.0
% water allocated to wet season	0.0	12.5	0.0	0.0	0.0
% change in expected utility from dry-season crop due to WD	30.6	60.7	0.0	30.6	30.6
% change in expected utility from wet-season crop due to WD	5.2	10.2	7.3	8.9	3.2
% change in value function due to WD	12.4	22.4	4.5	13.9	12.0
% change in total profit due to WD	17.2	19.5	0.0	20.3	14.6
% change in standard deviation of profit due to WD	21.6	10.4	16.9	52.0	21.2

Table 8. Sensitivity of Optimal Allocation Policies with Weather Derivatives (WD) to Changes in Parameters of Rainfall Distributions at the Module (α_1) and at the Reservoir α_2)

	Baseline Case ($\alpha_1 = 3.55$, $\alpha_2 = 10.25$)	50% Decrease in α_1 (Less in situ Rainfall)	50% Decrease in α_2 (Lower Reservoir Inflow)
Steady-state allocation level TCM/ha	1.21	1.09	0.93
% water allocated to dry season	100.0	62.5	100.0
% water allocation to wet season	0.0	37.5	0.0
% change in expected utility from dry-season crop	30.6	23.8	0.0
% change in expected utility from wet-season crop	5.2	1.3	23.3
% change in value function	12.4	8.0	13.4
% change in total profit	17.2	13.2	0.0
% change in standard deviation of profit due to WD	21.6	−21.6	0.22

Table 9. Sensitivity of Optimal Allocation Policies to Coverage Level of Weather Derivative Contract

	Baseline Case ($\theta = 100\%$)	$\theta = 90\%$	$\theta = 75\%$	$\theta = 50\%$
Steady-state allocation level TCM/ha	1.21	1.21	1.19	1.10
% water allocated to dry season	100.0	100.0	100.0	87.5
% water allocated to wet season	0.0	0.0	0.0	12.5
% change in expected utility from dry-season crop	30.6	30.6	30.6	15.5
% change in expected utility from wet-season crop	5.2	3.7	0.7	−0.9
% change in value function	12.4	11.3	9.0	4.1
% change in total profit	17.2	17.2	17.2	8.7
% change in standard deviation of profit due to WD	21.6	21.6	18.8	4.7

Furthermore, the overall allocation decreases, since the water authority needs to balance the needs of current production against future water demand. On the other hand, while decrease in reservoir inflow does reduce the overall allocation, it does not result in reallocation of water from dry to wet season. Instead, weather derivatives provide higher contribution to the expected utility of wet-season production.

Lastly, table 9 reports the sensitivity of optimal allocation policies to the coverage level of the weather derivative contract (equation 8). Lower coverage levels mean that weather derivatives are triggered at lower levels of precipitation and are thus less effective in reducing risk of drought. As a result, weather derivatives with lower coverage levels contribute less to the expected utility of wet-season production. Furthermore, when the coverage level is too low (50% of expected in situ rainfall), the water authority finds it optimal to allocate at least some water to wet-season production, since weather derivatives no longer provide adequate protection against precipitation shortfall.

The last lines in tables 6–9 also show the average profits for percentage change in standard deviation due to weather derivatives. By construction, results suggest that index insurance truncates the lower tail of the distribution. Accordingly, an increase in standard deviation of profits implies that there must be a significant increase in "upside risk" such that the upper tail of the distribution becomes thicker. Therefore, farmers would be enjoying "better good years" as well as income protection in bad years.[10]

[10] The average and standard deviation of profits for wet and dry seasons were also estimated. As expected, for all cases the average profit always increases when the weather derivative is included in the dry season. The standard deviations also show the same pattern, which implies that there must be an increase in "upside risk." For the wet season, the average profit decreases in most of the cases when the insurance is included (the maximum reduction is 6.5%). The standard deviation also shows a reduction, which implies that farmers' would reduce their risk when buying weather insurance during the wet season. These statistics are available upon request to the authors.

Concluding Remarks

In this paper, we assess the potential improvement in water allocation strategies that can be achieved using weather derivatives. We develop a stochastic dynamic optimization model of water allocation for dry- and wet-season crop production that explicitly incorporates farmers' welfare in water authority allocation decisions. The results demonstrate that the availability of weather-based insurance contracts reduces farmers' demand for water during the wet season and thus allows the water authority to reallocate water from the wet to the dry season. As a result, the expected utility of production in both seasons increases, as does farmers' welfare overall.

The results are robust to variations in the parameters of the model. An interesting result is that the weather derivatives can help to alleviate the effect of lower water availability at the reservoir as long as the distribution of rainfall at the farmer's location remains the same.

The analysis is based on a somewhat stylized model that in its present form considers several assumptions (e.g., producer homogeneity, single module, etc.) that could be somewhat limiting. However, the model can be enriched by relaxing all of the assumptions and calibrated to other specific locations within the same framework, albeit at a cost of additional model complexity.

In practice, implementing the proposed insurance scheme could require the modification of water rights. However, the water authority could implement several policies to deal with this issue, such as exchanging a portion of wet-season water rights for premium subsidies for the weather derivatives. This is not an unrealistic proposition, since users of irrigation districts informally trade their water rights even in developing countries with no functioning water markets.

Nevertheless, the results suggest that, given the surplus and welfare gains from implementing insurance, weather derivatives should be considered as a supplemental mechanism in water allocation decisions. Governments could support the operations of this scheme as an integral strategy against emergencies and disasters. They could also assist water authorities in developing the institutional features needed to provide weather insurance, such as legal and regulatory framework, data collection and management, training of insurance suppliers, and consumer education. Once weather insurance is working, it is likely to be an effective tool for improving water management in irrigation districts.

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