Downside Risk in Reservoir Management*†

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Abstract

Downside risk, which refers to deviations below a threshold, is often important in water management decisions, especially in areas with large and skewed variations in precipitation patterns. In this paper, we present a model for a reservoir manager who is downside risk averse and who performs a dynamic allocation of irrigation water, taking into account the negative effects of droughts on farm profits and different environmental constraints. We analyse the water stock, flows, and agricultural profits for alternative environmental restrictions and thresholds for irrigation levels and find that stricter environmental constraints increase total water supply and carryover stock, while higher penalty thresholds tend to lead to their overall decrease. Furthermore, increasing penalty thresholds leads to a higher emphasis on avoiding shortages, at the expense of lower average profits.

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Abstract: Downside risk, which refers to deviations below a threshold, is often important in water management decisions, especially in areas with large and skewed variations in precipitation patterns. In this paper, we present a model for a reservoir manager who is downside risk averse and who performs a dynamic allocation of irrigation water, taking into account the negative effects of droughts on farm profits and different environmental constraints. We analyse the water stock, flows, and agricultural profits for alternative environmental restrictions and thresholds for irrigation levels and find that stricter environmental constraints increase total water supply and carryover stock, while higher penalty thresholds tend to lead to their overall decrease. Furthermore, increasing penalty thresholds leads to a higher emphasis on avoiding shortages, at the expense of lower average profits.

1 Introduction

The natural variability of available freshwater resources is significant in many areas, with large deviations in seasonal and inter-annual precipitation patterns that often bring about serious problems for water users (which means, basically, for everyone). In arid and semi-arid places with established human populations, the most challenging issue is dealing with water scarcity and droughts, which represent the downside of natural variability in such areas. Wada et al. (2011) and Rodell et al. (2018) provide global assessments of water stress and freshwater availability trends, respectively, highlighting that population growth has heightened pressures on what is essentially a finite resource. Moreover, climate change is expected to decrease supply and exacerbate demand increases in several regions, through lower precipitation and higher temperature, while also bringing additional hydrological variability (Schewe et al., 2014). In these circumstances, the importance of including suitable risk analyses in water management decisions cannot be overstated.

Agriculture features prominently in water risk-management literature for two reasons. First, it is one of the main water users in many areas, often accounting for the majority of water withdrawals (in many countries, withdrawals for agriculture are around three quarters of the total).[1] Also, the sector is fraught with numerous sources of risk, including weather conditions as one of the most significant (Zhang and Antle, 2018). Thus the issue of risk management in agriculture has received considerable attention for decades (Just, 1975; Hazell and Scandizzo, 1977; Binswanger, 1982). A useful summary of the literature is OECD (2009). Nonetheless, Just (2003) identifies a need to refocus the analysis by emphasizing that farm-level and long-term risks are more relevant, and that methodological approaches that stipulate risk neutrality are inappropriate given the empirical evidence, which mostly favors the idea that farmers are risk averse. This is pointed out in the survey by Moschini and Hennessy (2001), which uses the expected-utility framework. More recently, a few studies have used questionnaires to provide a richer characterization of farmer attitudes using the theory of planned behaviour (Lynne, 1995; Bergevoet et al., 2004; Läpple and Kelley, 2013; Poppenborg and Koellner, 2013).

In this paper, we focus on the optimal water management problem of a benevolent supplier, who aims to maximize agricultural profits in a stochastic dynamic problem while recognizing downside risk (not enough irrigation may have severe effects below a certain threshold). Furthermore, the optimal management problem takes into account environmental constraints, such as set minimum levels of water that must be maintained in the reservoir. Using data from Turkey, we solve this model computationally to obtain the optimal carry-over stock (savings) and irrigation use, and then simulate the model to evaluate the effects of these threshold levels and environmental constraints on the key variables.

In many countries, such as Turkey, where our dataset is from, a benevolent agency is in charge of managing reservoirs. If a reservoir supplies water for many uses, decisions in case of shortages commonly resort to a prorating strategy . Urban (residential) use is often prioritized, which implies other uses such as agriculture may be prorated, depending on the severity of the shortage in a particular period. However, this strategy does not take into

[1] See FAO AQUASTAT.

account the dynamic nature of the problem or downside risk. Severe water shortfalls could have devastating results on the crop production, via either more land being left fallow or lower quality crops. Our model can provide some insight on how a manager may handle current shortages with an optimal allocation rule that avoids very undesirable outcomes over time.

Our contribution to the literature is twofold. First, we analyze the effects of downside risk on reservoir manager's decisions. In the relevant literature, Antle (1987) shows that the degree of downside risk aversion can be estimated and provides evidence for its occurrence among rice farmers in central India. Groom et al. (2008) confirm downside risk aversion in Cypriot farmers, highlighting that policy makers who misread farmers' risk preferences may obtain wrong predictions for the magnitude and even direction of input responses to water-use restrictions. Antle (2010) defends the use of lower partial moments to estimate asymmetric effects of inputs on agricultural production, a strategy pursued by Kim et al. (2014), where it can be seen that 90 % of the cost of risk on Korean rice farms comes from exposure to downside risk. Bozzola (2014) provides further evidence for downside risk aversion in Italian irrigation, noting that it is a key determinant in the decision to adopt new technology. Finally, Nauges et al. (2015) point out that different farmer groups seem to hold different attitudes to risk, with horticultural irrigators showing downside risk aversion. In our paper, we analyze the effects of setting different thresholds on the irrigation water use and agricultural profits over time, via changes in the mean as well as the shape of the distribution.

Second, we incorporate the *lower partial moments* (LPMs) into the stochastic problem to analyze the effects of downside risk over time. We assume that the manager allocates water under uncertainty across user groups while avoiding very low outcomes. The literature covers a number of instruments that target risk reduction, including efficient distribution (i.e., water-trading options and environmental-insurance contracts), increasing supply (i.e., desalination, external sources), and demand control (i.e., signals to farmers about potential risk to encourage changes in irrigation technologies or crop composition). Garrido and Gómez-Ramos (2009) provide a summary of economic instruments for drought management, while a more complete overview can be found in Lago et al. (2015). Gómez Gómez et al. (2018) point out the relevance of including institutional aspects in the economic analysis. In terms of specific instruments, Gómez-Ramos and Garrido (2004) discuss the potential of option contracts for efficient sharing of hydrological risks, whereas Vedenov and Barnett (2004) present weather derivatives as risk-management instruments for crop production. Meanwhile, water markets are an example of an instrument that increases water-use efficiency but also has risk-reduction potential, as shown in the work by Calatrava and Garrido (2005) and Zuo et al. (2015), both of which include estimates for downside risk.

Specifically for water reservoir management decisions, Howitt et al. (2005) find that a recursive-utility specification with risk aversion provided the best fit for the data on actual storage levels in a Californian reservoir. Tu et al. (2003), on the other hand, propose hedging rules that can be used during drought periods to improve the water allocation process. An application to water management can be found in Hanemann et al. (2016), which simulates the downside risk of climate change impacts in California. In our paper, we consider the changes in crop composition, motivated by the Turkish data, and examine to what extent accounting for the downside risk in the optimal water management problem affects results.

Our empirical results are threefold. First, we find that tighter environmental regulations do not necessarily have a negative impact on irrigation use, while the total supply and savings are affected positively. In our simulations, we observe that supply initially increases via higher savings, but flattens later once a certain level is maintained. Second, incorporating the LPM into the decision making process decreases the average agricultural profits, while lowering the variance as expected. Therefore, a severe shortage becomes less likely. Finally, we quantify how environmental constraints impact shortfall probability, expected shortfall, and semivariance. We find that tighter constraints slightly raise the shortfall probability and decrease the expected shortfall and semivariance.

2 Risk Measures and Attitudes

The production of adequate research on water-use choices under uncertainty requires the consideration of two distinct, if interrelated, aspects: the discussion (modeling) of different attitudes to risk (or, more generally, to uncertainty), and the definition of relevant risk measures.[2]

To evaluate the significance of randomness for actual choices, decision makers' attitudes towards uncertainty need to be understood. Typically, models in economic literature use expected utility theory, in spite of widespread criticism on many of its assumptions. Within the expected utility framework, attitudes toward risk can be characterized by the curvature of utility (risk aversion) and of marginal utility (downside risk aversion), as discussed in Menezes et al. (1980). Alternatively, downside risk aversion can be modeled through a utility function which penalizes results below the mean or some another reference point (Fishburn, 1977). The latter formalization can be related to the general phenomenon of loss aversion identified by Kahneman and Tversky (1979, 1992), even if it is still based on a framework of additive probabilities.

Meanwhile, risk measurement ranges from the simple calculation of variance (or standard deviation) to the analysis of stochastic dominance among distributions. *Variance* (signalling the dispersion of possible values around the mean) and the *coefficient of variation* (indicating the ratio of the standard deviation to the mean) are two simple ways to measure risk. However, both variance and the coefficient of variation place equal weights on observations on either side of the mean, so they may not be ideal measures if there is a concern for bad outcomes. If these are concentrated in the lower tail of a distribution, as is the case with water scarcity, the analysis calls for risk measures that focus on the downside risk, such as skewness, semi-variance, or other lower partial moments. When this downside risk is important, that is, when the placement of risk in a distribution matters, one possibly

[2]There are several ways to distinguish between risk and uncertainty, but the most common is to assume "risk" refers to a situation where probabilities are known and "uncertainty" to when they are not (Knight, 1921). In the paper we assume known probabilities and use risk and uncertainty interchangeably.

useful measure is *skewness*, which is the third standardized moment of a distribution. In particular, increases in skewness indicate that the probability mass is shifting to the left, so that downside risk is increasing. Nonetheless, it is still not a sufficiently general measure, since all moments of a distribution can matter.

An alternative approach is to measure downside risk by calculating LPMs. These are one-sided measures that look only at outcomes below a reference target value, $\underline{Q}$. The general expression for an LPM can be written as in Fishburn (1977):

$$LPM(\kappa_2, \underline{Q}) = \int_{-\infty}^{\underline{Q}} (\underline{Q} - q)^{\kappa_2} \; dF(q) \tag{1}$$

where $\kappa_2 \geq 0$ is the order of the partial moment and also reflects risk preferences in the below-target area, with $\kappa_2 < 1$ signifying risk-seeking attitudes, $\kappa_2 = 1$ representing risk neutrality (note that Eq.(1) becomes the expected value of the below-target outcome in this case) and $\kappa_2 > 1$ indicating risk aversion. The extreme case of $\kappa_2 = \infty$ implies that only the worst possible outcomes are considered. The most popular LPM are the target semi-variance and its special case, the mean semi-variance ($\kappa_2 = 2$ in both cases, but the target is specified as the mean in the latter).

Fishburn shows that there is a utility function whose maximization is congruent with LPM measures. It is an asymmetric function, as follows:

$$U(Q) = \begin{cases} Q, & Q \geq \underline{Q}, \\ Q - \kappa_1 \; (\underline{Q} - Q)^{\kappa_2}, & Q < \underline{Q}. \end{cases} \tag{2}$$

where κ_1 is a positive scaling term. Of all possible LPM measures, only target semi-variance is compatible with the formulation of Menezes et al. (1980), which establishes that downside risk increases unambiguously if a spread-contraction combination transfers risk to the left side of a distribution while preserving mean and variance. Nevertheless, LPM are very intuitive: in fact, Unser (2000) provides an experimental study which shows that, in a financial context, LPM are better at describing risk perceptions than variance. However, the author also stresses the importance of framing effects and of the simple probability of a below-target return ($\kappa_2 = 0$).

Finally, it is worth noting that another financial risk measure that would be easy to interpret even for complex portfolios is *value-at-risk*, which is a threshold value in monetary units such that the probability mass of getting losses greater than the threshold over a given (short) period is some specified number (typically 1% or 5%). Thus, if value-at-risk increases at a given confidence level, the expected potential losses for the period are growing, and therefore there is more risk. Since it only looks at losses, value-at-risk clearly belongs in the family of downside risk measures. However, as it only considers one specific quantile, it is not appropriate for ranking distributions.[3]

3 Reservoir Management Model

In this section we present the model that will be used to assess different assignation rules between agriculture and environmental requirements in a surface water reservoir. We consider a benevolent agent to manage the water supply, such as a water user association (WUA) or a local government body, and refer to this as the *reservoir manager*.

While water levels in a reservoir are measured at regular intervals, future levels are random from the point of view of the reservoir manager, since they depend on run-off, which determines reservoir filling. In the Mediterranean region water levels are highly seasonal. Precipitation occurs mostly in winter and early spring, and is almost nonexistent during the summer and early fall. Precipitation increases the water supply for all user groups (via inflows to the reservoir) and it could partially (sometimes fully) offset the demand for irrigation. However, the irrigation season usually starts in late spring and continues until autumn, so it does not coincide with the main filling period in a typical hydrological year,

[3] A broader view of risk is embedded in the concept of stochastic dominance, surveyed in Levy (1992). This includes stochastic-dominance results based on the quantile approach.

defined from October until September of the following year. Given the characteristics of the region, we assume in the model that precipitation is not available when irrigation is needed; we will demonstrate these features of the data in Appendix Section A.[4]

3.1 Agricultural Profits

Models of reservoir management for agriculture commonly assume that profits vary with the amount of irrigation water in a risk-neutral manner:

$$\Pi(Q) = \sum_{c=1}^{N} p_c \ \alpha_c \ L_c \ \min(Q_c/\gamma_c, 1) \tag{3}$$

where the agricultural profits $\Pi(Q)$ include the profits from every crop c. These in turn depend on the crop price p_c, land productivity α_c, crop water requirement γ_c, land allocated L_c, and the amount of water allocated Q_c.[5]

Different from the above formulation, we wish to exploit the possibility that farmers have downside-risk aversion so there is a disutility term when the irrigation water falls below a certain threshold. As a result, similar to (2), the utility from profits equals:

$$\widetilde{\Pi}(Q, \underline{Q}) = \begin{cases} \Pi(Q), & Q \geq \underline{Q}, \\ \Pi(Q) - \kappa_1 \ \left[\Pi(\underline{Q}) - \Pi(Q)\right]^{\kappa_2}, & Q < \underline{Q} \end{cases} \tag{4}$$

where $\underline{Q}$ represents the threshold level, κ_1 is some positive scaling term, and κ_2 controls the risk preferences below the threshold area.

It is noteworthy that the limits in (4) are defined in terms of quantity (i.e., the amount of irrigation Q) instead of profits (i.e., $\Pi(Q)$), assuming that the profits are non-decreasing

[4] While we make this assumption to better fit the data, we could further revise the model to allow for this substitution in other datasets/regions where such a link exists.

[5] Water prices are not included in the model, because the solution to the reservoir manager's optimization problem defines the quantity of irrigation water. It would be possible to calculate implicit shadow values to be used as prices, instead of directly regulating quantity, if the regulatory framework called for a price strategy. Additionally, we model the farmer's land allocation decision as a discrete choice problem here but we will focus on the implications of the model on water management decisions for brevity.

in quantity. Consequently, the utility functional form is congruent with the lower-partial-moments (LPM), where the profits increase linearly in Q if the irrigation use is above the threshold, but they incur a penalty if available water is below the threshold.

3.2 Environmental Constraints

Environmental constraints to reservoir levels most often exist as a way to maintain adequate flows in river ecosystems. The establishment of a flow regime is complex and context-specific. There is not a single best way of doing it, although dams clearly play a significant role; see Dyson et al. (2003).

We adopt the term $E(S)$ to represent the environmental constraints, which may depend on the currently available water supply. We consider absolute and relative stock restrictions to examine the effects of different environmental requirements. With the absolute restrictions, there is a *fixed threshold* of carryover stock: any volume above it can be used for consumption (or simply released to avoid overflows). With the relative restrictions, the reservoir manager splits water reserves, allotting *a proportion* of available volume to environmental uses as water levels increase. Either way, we assume that the stock that is carried over will be available in future periods to be released as environmental flows, if necessary.[6]

3.3 Water Management Problem

We first introduce some notation about the key components of the model. Water supply available in period (year) t is denoted by S_t, which is a function of the carryover stock from last period (w_t), and stochastic recharge (R_t). This supply is allocated to four uses. Urban water use (U_t) is not expected to vary significantly with hydrological conditions, thus we treat it as constant throughout the paper ($U_t = U$). The second component (F_t) is the

[6] While we model the time period as a year in this paper, one could alternatively consider monthly variations in stochastic variables and their effects on the amount of monthly irrigation and savings. Furthermore, a monthly analysis with detailed data could provide more insight by allowing the environmental flows to change throughout the year.

amount of water released to avoid overflows, which is only relevant during periods with high inflows (when no irrigation is happening anyway) and has no economic return (except for avoiding damages). We model F_t as a function of the stochastic recharge. The third use is for irrigation (Q_t), which is one of the control variables in our model. The last component is the carryover stock (w_{t+1}), which provides the dynamic link between periods.

Our timeline is as follows: at the beginning of the irrigation season, the reservoir manager observes the carryover stock and the recharge, to calculate the water supply. Taking into account urban water use and existing environmental constraints, the manager chooses the value for irrigation water (Q) to let farmers know how much water will be available to them in the coming months. The farmers then make crop choices that match their aggregate demand for irrigation to the amount declared by the reservoir manager. Depending on how much water is available, some percent of the land may be left fallow. The remaining supply is saved as carryover stock for the next period.

The reservoir manager aims to maximize the expected discounted utility of profits from agriculture subject to two constraints:

$$\sum_{t=0}^{\infty} \beta^t \underset{R_t}{\mathbb{E}} \left[\widetilde{\Pi}(Q_t, \underline{Q}) \right] \tag{5}$$

$$\text{Resource Constraint: } S_t = S(w_t, R_t) = U + F_t(R_t) + Q_t + w_{t+1}; \forall t = 0, 1, \dots \tag{6}$$

$$\text{Environmental Constraint: } w_{t+1} \geq E(S_t); \forall t = 0, 1, \dots \tag{7}$$

$$\text{Initial State: } w_0 \text{ is given.} \tag{8}$$

where the first constraint (6) governs the evolution of the water stock: The left-hand side of this equation is the total supply of water (S), which depends on savings from last period (w) and stochastic recharge (R), while the right-hand side reflects all uses (U, F, Q), including the carryover stock (w'). The second constraint (7) is due to environmental protection, which is imposed as a lower bound on carryover stock (w_{t+1}).

Given the recursive nature of the problem, we can rewrite it as a Bellman equation:

$$V(w, R) = \max_{w', Q} \widetilde{\Pi}(Q, \underline{Q}) + \beta \mathop{\mathbb{E}}_{R'|R} [V(w', R')] \tag{9}$$

$$S(w, R) = U + F(R) + Q + w' \tag{10}$$

$$w' \geq E(S). \tag{11}$$

where the value function $V(w, R)$ depends on the two state variables (w, R), which denote the carryover stock and stochastic recharge. The expectation operator $\mathop{\mathbb{E}}_{R'|R}(\cdot)$ is due to the uncertainty in future recharge levels, which may follow a known Markovian distribution that is conditional on the current recharge (R).

It is worth noting that the environmental constraint provides a lower bound on the carryover stock. In other words, in a situation where the savings appear to be less than the environmental constraints (i.e., $w' < E(S)$), the reservoir manager prorates the irrigation water use until the constraint is met.[7] The rationing of irrigation water implies that the agricultural profits decline accordingly.

Before we move onto the numerical illustration, it may be useful to describe how the solution will depend on some of the key parameters. A higher recharge implies higher water supply, which allows the manager to increase savings (carryover stock) as well as irrigation. On the other hand, an increase in the penalty threshold might lead to higher irrigation and lower carryover stock. Finally, a tighter environmental constraint imposes a higher amount that must be saved. As a result, during drier periods, the manager is forced to save more for the future, cutting down irrigation.

[7]This assumption, while not necessary for the solution, is motivated by the data. In case of a shortage, irrigation use is most often pro-rated, while residential use is not affected as much in the data; see Figure 1.

4 Numerical Illustration

Since the dynamic problem given in (9)–(11) is stochastic, it is more practical to illustrate the solution numerically rather than seek an analytical solution. We use data from Turkey to calibrate the key parameters of the model. These values are provided in Table 1. We refer to the Appendix Section A for further details on the data description and parameter estimation.

The State Waterworks are in charge of managing the reservoirs in Turkey. They determine how much water to allocate for urban (residential) and irrigation uses. Once the amounts are set, municipalities run urban water management while WUAs handle irrigation. To do so, they report how much water is available to all farmers at the beginning of the season and then record crop choices for the agricultural area. Finally, the WUAs then decide on the amount of water to be allocated for each crop and the corresponding irrigation price.

It is worth noting that we do not entertain this decentralised structure in our model for two reasons. First, water prices are considered as *fees* to balance the budget, thus they do not reflect scarcity value and in the case of agriculture, they are per area pricing. Second, the municipalities and WUAs do not have much control over the amount of water allocated across various user groups.

In case of shortage, the State Waterworks prioritizes urban water use. Therefore, it is relatively steady in the data (after controlling for the population increase). This implies that any possible cuts are in agricultural use, as illustrated in Figure 1. In most cases, the land allocated for wheat experiences the most severe cuts, since wheat (relative to cotton, sugar beet, and maize) has the lowest crop water requirement in the region. However, this strategy of prorating agriculture in each period does not take into account the dynamic nature of the problem or the downside risk.

The dataset used in this analysis is from South-Southeastern Turkey, and reports the aggregate allocation of agricultural land (of about $20,000$ha) from 1984 to 2007 across four crops (including leaving the land fallow). The crop composition over time is illustrated in

Figure 2. According to this figure, there is a significant change in the crop composition over time in that: (1) The proportion of land allocated for cotton has reduced significantly (from as high as 90% to as low as 15%) over time, (2) Maize has emerged in late 1990s as a lucrative option for land allocation, (3) The proportion of land left fallow has increased in late 1990s and early 2000s (it peaked at more than 20% in 2001), mostly due to the severe water shortages experienced in the region.

To estimate agricultural profits (3), we set up a Logit model, where a representative farmer takes into account the crop prices, water availability, and land productivities and makes the land allocation decision over these four crops (cotton, maize, sugarbeet, and wheat). Leaving some part of the land fallow is also an option (of last resort with no economic benefits), unless enough water is available for irrigating the whole area.

The threshold levels ($\underline{Q}$) are not considered in the data generating process. To investigate the effect of different thresholds on the variables of interest (i.e., irrigation use, total and carryover stocks), we try threshold levels so that, based on the crop choice decision by farmers in (3), the proportion of land left fallow equals $\{10\%, 20\%, 25\%\}$. Consequently, the corresponding threshold levels are set to $\left\{\underline{Q}3 = 152, \underline{Q}2 = 121, \underline{Q}1 = 109\right\}$ (in hm^3), respectively.[8]

As indicated in Table 1, reservoir capacity ($\bar{w}$) is fixed at 173.173hm^3 and the minimum historical carryover stock is constant at 5.65hm^3. We assume, as discussed in Section 3, that the carryover stock is bounded below by an environmental constraint ($\underline{w} = E(S)$). We consider four cases here: (EC1) $E(S)$ is constant at 5.65hm^3, (EC2) $E(S)$ is constant at 11.30hm^3, (EC3) $E(S)$ is proportional to total supply at 5%, and (EC4) $E(S)$ is proportional to total supply at 10%. These environmental constraints provide alternative minimum levels for the carryover stock. The stricter the environmental constraint, the more conservative the reservoir manager, saving more water for the future while making less available for irrigation use.

[8] We could consider alternative values for thresholds, but the values used in the analysis already yield dramatic changes to land use decisions.

Since we do not observe the downside risk preferences in the data, we set the parameters κ_1 and κ_2 to 20 and 2, respectively. The choice of the value for κ_2 is to make the use of LPM consistent with the utility framework in (2). Having done so, we have tried various values of κ_1 and adopted a value that would make the penalty severe enough for the effect of LPMs to arise in the numerical illustration.

We define the *Benchmark* case (i.e., $\underline{Q}0 = 0$) as one with simple risk neutrality (without a threshold). For each environmental constraint (EC1–EC4) and penalty threshold level ($\underline{\text{Q}}$0–$\underline{\text{Q}}$3), the reservoir manager optimally chooses the irrigation use (Q) to maximize the sum of the expected discounted agricultural profits, defined as a value function in (9), subject to resource and environmental constraints, given in (10) and (11). Given the state variables in carryover water stock, stochastic inflows, and stochastic crop prices, we use the grid-search method to compute the value function in *MATLAB*.

Once we compute the value and policy functions, we perform a Monte-Carlo simulation, running the model 1000 times for 25 years. The choice of 25 years is not arbitrary; the variables of interest converges to their long run targets by this period. In our analysis, we focus on three key variables: total supply (S), carryover stock (w'), and irrigation water (Q). First, in Section 4.1, for each environmental constraint and threshold level, we calculate the mean of these variables in selected periods and compare the effect of the threshold level against a *benchmark* model, which has no penalty threshold ($\underline{Q}0 = 0$). Then, we evaluate the cost of threshold levels and environmental constraints on the agricultural profits in Section 4.2. Finally, in Section 4.3, we return our attention to LPM measures for irrigation use and calculate shortfall probability, expected shortfall, and semi-variance over time, across different penalty thresholds and environmental constraints.

4.1 Monte-Carlo Simulations: Summary Statistics

This section presents the results from the Monte-Carlo simulation of our reservoir model, specifically for the irrigation use (Q), total supply of water (S), and carryover stock (w'). To understand how these three variables evolve over time, we simulate the stochastic recharge and crop prices, and employ the optimal policy rules to calculate the three variables in each period of the simulation. While a low value for the carryover stock (eg., $w_0 = EC1$) would create a severe shortage at the beginning of the simulation and produce more dramatic results, we assume that the starting carryover stock in period 0 is set to the median in the data ($w_0 = 41.78$), so the results are consistent with the values in the data. As mentioned above, we simulate the model for 25 periods so that we can find out the long run targets of these three variables.

We compare our results across different environmental constraints and thresholds. To do so, with each of the four environmental constraints, we calculate the mean of the simulated variables (irrigation water, carryover stock, and total supply of water). The *benchmark* model refers to the case where there is no threshold imposed, so no penalty is applied to manager's utility (i.e., $\underline{Q}0 = 0$ in (4)). Table 2 presents the average values (across simulations) of the three variables in selected periods for each environmental constraint and threshold level.[9]

We start our analysis with the effect of environmental constraints, which present a restriction on the lower bound of savings, so the more restrictive an environmental constraint is, the lower the irrigation use is on average. While our results in Table 2 verify this finding, the decrease in irrigation use is not statistically significant across environmental constraints: the mean irrigation use is around 130hm^3. However, time profiles will be different. The main effect of environmental constraints is on the total supply via the carryover stock (savings). The mean carryover stock increases overall when the environmental constraint is more restrictive: in our case, the direction of increase is from constant values (EC1 and EC2) to percent values (EC3 and EC4). For instance, in the benchmark model, the total supply increases from 289hm^3 with EC1 to 304hm^3 with EC4, along with the carryover stock (63hm^3 to 78hm^3).

When we focus on the effects of increasing threshold value, again we find that the ir-

[9] Other summary statistics are also calculated but not presented here for brevity.

rigation use is not affected significantly. Meanwhile, the carryover stock and total supply decrease with the threshold value across all environmental constraints. For instance, with EC1, the average total supply increases from 257hm^3 with $\underline{Q}3$ to 262hm^3 with $\underline{Q}2$, 288hm^3 with $\underline{Q}1$, and finally to 289hm^3 with no threshold level. As the threshold value is relaxed, the manager can afford to supply agriculture with less irrigation, so more can be saved as carryover stock, increasing the water supply.

Table 2 also provides insights about the evolution of these three variables over the periods. In general, we observe that, in the earlier periods (i.e, period 5), the reservoir manager aggressively saves more for the future (see the high carryover stock in period 5), while trying to stay close to the threshold. Over the periods, the reservoir manager accumulates enough stock (see periods 10–25), so carryover stock goes down and more water can be released for irrigation use.[10]

To summarize, across the four types of environmental constraints with varying thresholds, we can conclude that changing the environmental constraint to a more conservative one unambiguously increases the total supply, but has little effect on irrigation use. Also, the increase in threshold level mainly drives up the total supply via carryover stock. For instance, from a high threshold ($\underline{Q}3$) to no threshold, the total supply increases by around 12% (from 257hm^3 to 289hm^3 with EC1). Finally, the carryover stock is higher in earlier periods, signaling an initial increase in total supply, and then it levels off (often by period 10–15). Given that we start with the median value for the carryover stock in period 0, the variables appear to have converged to their long run target distribution by period 25.

[10]In the benchmark case with no threshold and the case with low threshold ($\bar{Q} = 109$), the manager appears to be overaggressive in saving the carryover stock for the future periods. This result is due to two factors. On the one hand, the initial condition is lower than the long run value, which leads to a build up of carryover stock, particularly to avoid the adverse effects of potential low inflows in the future. The second factor is the bimodal feature of the distribution of the total supply, which leads to either very low or high values for carryover stock. This behaviour disappears after the first few periods in these two cases and is not at all present for the other two, with higher threshold levels.

4.2 Monte-Carlo Simulations: Agricultural Profits

In Table 3, we analyze the implications of the environmental constraints and threshold levels on the sum of expected discounted agricultural profits (which we will refer to as *total profits*). It is important to note that the values do not take into account the penalty term.

The agricultural profits are highest in the benchmark model (4.11TRY (Turkish lira in real terms) with EC1), compared to threshold levels (e.g. 2.66TRY in $\underline{Q}2$ and 2.22TRY in $\underline{Q}3$), but often at the cost of higher variation.[11] The main reason for this result is that the benchmark model includes no threshold, so it maximizes the agricultural profits (not the profits minus the penalty). However, the manager is also more prone to shortages in the benchmark model. To reduce the frequency and severity of these shortages, the reservoir manager can utilize the threshold levels ($\underline{Q}1$–$\underline{Q}3$), but at the cost of lower averages. Consequently, we can attribute the changes in the agricultural profits as the cost of thresholds. For instance, from the benchmark model to $\underline{Q}2$, the average agricultural profits decrease by about 35% for all environmental constraints, while it further goes down by 16% from $\underline{Q}2$ to $\underline{Q}3$. Meanwhile, having a higher threshold level decreases the shortfall probability and variance below the threshold (which will be discussed in Section 4.3).

The stricter environmental constraints decrease the *total profits*: relative to EC1, EC2 decreases the total profits by 1.26–1.86%, whereas EC4 reduces by at least 6.8% for all but $\underline{\mathrm{Q}}3$. The effects of environmental constraints is less pronounced in $\underline{\mathrm{Q}}3$, since the threshold ($\underline{\mathrm{Q}}3$) is already at a high level (and so the variation is already reduced considerably).

4.3 Monte-Carlo Simulations: Lower Partial Moments

While the average irrigation use seems to be fairly stable across different environmental constraints and thresholds over time (see Table 2), it would be misleading to conclude that these factors have no effects at all on irrigation. Therefore, we calculate the lower partial moments of the irrigation use, and assume that parameter κ_2 equals $\{0, 1, 2\}$ in (1). These three

[11] 4TRY is roughly equal to 1USD.

cases corresponds to *shortfall probability*, *expected shortfall*, and *semi-variance*, respectively.

The shortfall probability is the probability of irrigation use going below the threshold, while the expected shortfall is the average difference between the threshold and irrigation use, conditional on the irrigation use being lower than the threshold, implying the magnitude of the shortages when they occur. The semi-variance, similar to the variance measure, signals the variation in the shortages when they occur. For instance, according to Table 4, with $\underline{Q}1$ and EC1, the average shortfall probability over all periods is 0.68 indicating that in 68 percent of the time, the amount of water given to farmers will be less than the threshold level of 109hm^3. In this case, the irrigation use is on average 20.53hm^3 less than this threshold, with semi-variance equal to 1229hm^3 (semi-variance).

Table 4 lists these three measures for the irrigation use across different environmental constraints and thresholds for selected periods. When the threshold is high (i.e. $\underline{Q}2$ or $\underline{Q}3$), it is expected that the shortfall probability will be high. In fact, with $\underline{Q}3$, it is almost impossible for the manager to irrigate at or above the threshold in any period. As the threshold decreases (from $\underline{Q}3$ to $\underline{Q}1$), the average shortfall probability over all periods goes down: with EC1, it is 67% with $\underline{Q}2$, and 34% with $\underline{Q}3$.

When we consider different environmental constraints, we see that the average shortfall probability decreases in earlier periods, but increases eventually, but mostly stays the same overall (i.e., from 67% with $\underline{Q}2$ and EC1 to 71% with EC4). [12]

To explore the effect of the threshold level on the expected shortfall ($\kappa_2 = 1$), we first revisit our definition of the expected shortfall given in (1):

$$LPM(\kappa_2 = 1, \underline{Q}) = \int_{-\infty}^{\underline{Q}} (\underline{Q} - q)\ dF(q, \underline{Q}) \tag{12}$$

where $F(q, \underline{Q})$ denotes the cumulative distribution function of irrigation use q, which has

[12] The average shortfall probability with $\underline{\text{Q}}2$ in EC1 is 67%, whereas the four periods depicted in this table have all higher probabilities. It is worth noting that in the earlier periods, the shortfall probability is much lower (not illustrated here), which leads to this average value. The opposite is true for EC4, where, in the earlier periods, the shortfall probability is higher, so the mean is higher than the four periods depicted on Table 4.

a probability density function denoted by $f(q, \underline{Q})$. Equation (12) is slightly different than (1). In (1), the cumulative distribution does *not* depend on the threshold, so increasing the threshold cannot decrease the expected shortfall. Meanwhile, in (12), the cumulative distribution $F(q, \underline{Q})$ also depends on the threshold level, given the dynamic nature of the problem, as the optimal rule for carryover stock changes with the threshold. Consequently, this further impacts the distribution of the irrigation use. To investigate the effect of the threshold on the expected shortfall, we compute the partial derivative of the expected shortfall with respect to threshold level:

$$\begin{aligned}\frac{\partial LPM(\kappa_2 = 1, \underline{Q})}{\partial \underline{Q}} &= \frac{\partial}{\partial \underline{Q}} \left(\int_{-\infty}^{\underline{Q}} (\underline{Q} - q) \; dF(q, \underline{Q}) \right) \\ &= \int_{-\infty}^{\underline{Q}} f(q, \underline{Q}) \; dq + \int_{-\infty}^{\underline{Q}} (\underline{Q} - q) \; \frac{\partial f(q, \underline{Q})}{\partial \underline{Q}} \; dq. \end{aligned} \tag{13}$$

Equation (13) implies two effects of the threshold on the expected shortfall. On the one hand, the higher the threshold, the more likely the irrigation use is to stay below the threshold, so the expected shortfall increases. This effect is due to the first term on the right hand side and also present in (1). On the other hand, when the threshold is larger, the distribution also changes (via the first term on the right hand side), because the reservoir manager revises the optimal carryover stock, which further affects the total supply in the next period. Thus, it is not clear if the overall effect is positive or negative.

As can be seen in Table 4, the shortfall probability is relatively high for thresholds $\underline{Q}2$ and $\underline{Q}3$, so the first effect dominates the second. Consequently, the expected shortfall goes down when the threshold is lower (from $\underline{Q}3$ to $\underline{Q}2$). Meanwhile, the shortfall probability is relatively low for threshold ($\underline{Q}1$). In this case, the expected shortfall stays high compared to the threshold $\underline{Q}2$, indicating that while irrigation use is less likely to fall below the thresholds, the difference is high when it occurs.

The effect of environmental constraints on the expected shortfall is not as pronounced. While the environmental constraints do not appear to change the expected shortfall significantly in the case of $\underline{Q}3$, the stricter constraints tend to lower the expected shortfall with lower thresholds. This pattern is similar but more significant for semivariance.

To summarize, we find that the shortfall probability increases with the threshold level, while environmental constraints do not have a significant effect overall. Meanwhile, we distinguish the two effects of the threshold level on the expected shortfall: the first one is the direct effect and the second one is via the change in the policy rule. We conclude that an increase in the threshold level initially decreases the expected shortfall (since the second effect dominates), but eventually increases it (via the first effect). A similar pattern is also observed in the semi variance values. Meanwhile, tighter environmental constraints generally decrease the expected shortfall and semivariance.

5 Concluding remarks

This paper sets out to analyze the risk profiles of different assignment rules and environmental constraints in a water reservoir that serves agricultural demand for irrigation. We present a model for a downside risk-averse reservoir manager in order to examine how the optimal savings and irrigation use react to different assignment rules and increasingly demanding environmental constraints. To conduct our analysis, we incorporate the lower partial moments into our dynamic model, as they put more emphasis on the shortages. Since these are a key issue in water management in many irrigated areas, we believe the use of one-sided risk measures should be more widespread. Using Turkish data, we solve our model computationally and simulate it to evaluate the effects on irrigation use, total supply, and carryover stock, as well as agricultural profits.

The results are quite intuitive. First, we conclude that while thresholds (for LPM) and environmental constraints do not impact the average irrigation use, total supply and carryover stock are affected positively by stricter environmental constraints and negatively by increasing thresholds. As environmental constraints get stricter, carryover stock has to be maintained at a higher level, which raises the total supply. On the other hand, increasing thresholds mean the utility penalty is stronger, so more water is allocated to irrigation.

Second, agricultural profits decrease with higher thresholds and stricter environmental constraints. On the one hand, thresholds put more emphasis on avoiding shortages, so the variance may go down at the expense of lower average profits. Tighter environmental constraints, by forcing higher savings, decrease profits.

Third, we find that as the threshold increases, the shortfall probability increases. Meanwhile, for a given threshold, stricter environmental constraints slightly raises the shortfall probability. However, the effect of thresholds on the expected shortfall and semivariance is not clear, as the dynamic problem will take the threshold into account, so the distribution of the irrigation use changes with the assumed threshold level. Meanwhile, the environmental constraint have a negative impact on the expected shortfall, which is more pronounced in the semivariance.

Extensions to this research could include modeling the distribution of stochastic recharge as a Markov process, or utilizing its empirical distribution. Additionally, the model could include multi-purpose reservoirs with hydropower production, as well as more realistic environmental flow regimes. Another interesting avenue for further research would be to compare the results of our single-goal optimization model to those of more realistic, and complex, hydroeconomic models of water management where multiple attributes are considered (Rausser and Yassour, 1981; Delforce and Hardaker, 1985; Gómez-Limón and Riesgo, 2004; Chung and Lee, 2009). The advantage of this approach is that one goal is not paramount and decision weights take center stage. Participatory methods (Munda, 2008; Messner et al., 2006; Paneque Salgado et al., 2009) can be used to select attributes and weights as well as enable better policy discussions.

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A Data Description

Water data presented here are from the Kartalkaya dam, located in the Ceyhan basin in south-eastern Turkey. It provides water for irrigation and drinking purposes. The dam capacity is 173.173 hm^3 and the total irrigation area that it serves is $22,810$ha (Pazarcik County). It also supplies tap water to the city of Gaziantep (population of 1.5 million).

Data concerning the flows into the Kartalkaya dam are available from January 1984 to August 2007 (with a total of 284 observations), and the boxplot of the flows (in hm^3) are depicted in Figure 3. Since precipitation is mostly during the winter, reservoirs are required to provide water for summer irrigation. The government releases water for three purposes: tap, irrigation, and to avoid reservoir overflows. Tap water use amounts to around 100 hm^3 annually; irrigation use is slightly higher, ranging between $130 - 150$ hm^3. Water released to avoid overflows does not have any other economic benefit.

Agriculture in general may make use of precipitation as a substitute for irrigation. However, we assume precipitation is not a viable source when irrigation is needed, which is often the case for semi-arid and arid regions. Therefore, Q_t measures the amount of irrigation during a period (from October to September).

Water released to avoid overflows is censored from below: it is zero if there is no threat of overflows; also, more water than the reservoir capacity may be released in any given year. Therefore, we estimate the water release for flood control, denoted by F, using the Tobit model and utilizing the annual recharge R as the predictor.

To solve the dynamic problem, we assume that the exogenous stochastic shocks in this economy stem from two components: inflows to the reservoir and crop prices. We estimate the annual inflows with an auto-regressive process, but reject the test for autocorrelation. Therefore, we fit the inflows data with the Gamma distribution.[13]

Among the crop prices, only the crop price of cotton has changed significantly over the

[13] See Heidecke and Heckelei (2010); Leizarowitz and Tsur (2012) for the use of Gamma distribution to estimate inflows.

last two decades. Meanwhile, the crop prices of wheat, maize, and sugar beet have stayed almost constant during the time period. To incorporate these stochastic shocks, we assume a log-normal distribution for the crop price of cotton, estimate an AR(1) process, and derive the transition matrix using the algorithm described by Tauchen (1986).

Table 1: **Parameter Values for the Empirical Illustration**

Type	Parameter	Variable	Value
Computational	Carryover stock: grid points	N_w	100
	No of periods in each simulation	N_T	25
	No of simulations	M	1000
LPM	Penalty scalar	κ_1	20
	Order of partial moment	κ_2	2
	Penalty thresholds[a] (hm^3)	$\underline{\text{Q}}1$–$\underline{\text{Q}}3$	$\{109, 121, 152\}$
Uncertainty	Stochastic recharge: no of grid points	N_R	8
	Stochastic recharge: distribution (hm^3)		Gamma$(5.6910, 69.2267)$
	Cotton price: no of grid points	N_p	2
	Cotton price: distribution		AR(1)
Economic	Discount rate (%)	r_β	1%
	Minimum carryover stock (hm^3)	$\underline{w}$	5.65
	Maximum carryover stock (hm^3)	$\bar{w}$	173.173
	Env. constraints: fixed (hm^3)	EC1–EC2	$(5.65, 11.30)$
	Env. constraints: variable (% of supply)	EC3–EC4	$(5\%, 10\%)$
Water Use	Residential demand (hm^3)	U	95.32
	Flood Prevention (hm^3)	F	$\max(-220.91 + 0.9695\ R, 0)$

Note: [a] The threshold values for the irrigation water use are chosen so the proportion of land left fallow equals $\{25\%, 20\%, 10\%\}$, respectively.

Table 2: **Summary Statistics (Mean) of Key Variables (in hm^3) in the Simulation**

		Irrigation Use - Mean				Total Supply - Mean				Carryover Stock - Mean			
	Period	EC1[a]	EC2	EC3	EC4	EC1	EC2	EC3	EC4	EC1	EC2	EC3	EC4
Benchmark[b]	5	87.77	88.00	92.20	137.17	267.65	269.26	272.83	310.89	84.48	85.85	85.22	78.03
	10	129.71	123.68	125.94	128.16	292.72	291.15	293.22	301.70	67.52	71.97	71.79	77.95
	15	136.23	129.15	129.15	131.11	292.55	293.08	293.93	304.18	60.84	68.43	69.28	77.46
	25	138.86	137.23	138.36	130.51	295.93	297.49	299.15	303.71	61.56	64.73	65.26	77.59
	Overall[c]	130.72	130.58	130.55	129.96	288.87	292.99	294.28	303.69	62.66	66.90	68.22	78.12
$\underline{Q}1$=109[d]	5	88.60	101.89	115.42	141.99	269.01	278.05	288.70	309.32	85.04	80.75	77.85	71.88
	10	134.55	130.13	130.38	128.22	295.19	293.52	294.60	301.24	65.19	67.94	68.77	77.59
	15	141.65	132.97	132.01	128.54	294.07	293.49	294.13	299.81	56.96	65.08	66.69	75.84
	25	136.57	135.39	134.40	133.42	292.91	295.37	296.13	302.97	60.88	64.52	66.26	74.11
	Overall	130.79	130.64	130.57	130.28	287.73	292.08	293.75	301.24	61.49	65.99	67.73	75.53
$\underline{Q}2$=121	5	115.33	126.16	130.30	143.29	251.28	263.94	267.30	296.54	40.61	42.45	41.66	57.88
	10	121.88	127.82	130.21	136.70	255.60	265.92	267.66	291.66	38.38	42.75	42.10	59.58
	15	126.68	130.10	130.50	135.13	257.79	267.46	268.12	290.16	35.77	42.02	42.27	59.66
	25	129.66	130.28	131.06	133.50	260.68	267.56	269.89	290.05	35.68	41.94	43.49	61.18
	Overall	131.91	131.65	131.59	130.86	262.10	269.83	271.01	288.13	34.86	42.83	44.08	61.91
$\underline{Q}3$=152	5	132.86	131.65	131.53	131.13	260.30	261.28	261.53	268.13	32.12	34.30	34.68	41.68
	10	131.07	130.87	130.84	130.08	255.49	259.17	259.88	269.66	29.10	32.98	33.72	44.26
	15	130.84	130.94	130.98	130.71	253.70	259.02	259.88	271.53	27.54	32.76	33.58	45.50
	25	132.13	131.60	131.54	131.46	252.14	258.03	258.49	271.48	24.69	31.10	31.63	44.70
	Overall	132.36	132.11	132.08	131.56	256.89	260.88	261.45	270.97	29.21	33.45	34.04	44.08

Note: $^{(a)}$ The notation "EC1–EC4" refer to the environmental constraints for the *minimum* carryover stock: (EC1) constant at 5.65hm^3, (EC2) constant at 11.30hm^3, (EC3) variable with 5% of the supply, (EC4) variable with 10% of the supply. $^{(b)}$ The "Benchmark" model refers to the case where there is no penalty threshold. $^{(c)}$ The term "Overall" indicates the average over all periods. $^{(d)}$ The notation "$\underline{Q}1$–$\underline{Q}3$" refer to the threshold levels of the irrigation use that lead to $\{25\%, 20\%, 10\%\}$ of the land left fallow, respectively.

Table 3: **Average Discounted Lifetime Agricultural Profits (without Penalties)**

	Average[a]				Std. Dev.				% change (rel. to EC1)			
Period	EC1[b]	EC2	EC3	EC4	EC1	EC2	EC3	EC4	EC1	EC2	EC3	EC4
Benchmark[c]	4.11	4.06	4.03	3.83	0.28	0.28	0.28	0.26	0	-1.26	-1.92	-6.8
$\underline{Q}1 = 109$[d]	4.11	4.03	3.97	3.62	0.28	0.28	0.28	0.29	0	-1.86	-3.43	-11.76
$\underline{Q}2 = 121$	2.66	2.62	2.58	2.43	0.34	0.35	0.35	0.36	0	-1.7	-2.88	-8.74
$\underline{Q}3 = 152$	2.22	2.2	2.2	2.16	0.19	0.18	0.18	0.18	0	-0.72	-0.92	-2.79

Note: $^{(a)}$ The term "Average" indicates the average, across simulations, of the sum of the discounted lifetime agricultural profits, measured in real terms of the domestic currency. This measure does not account for the penalty if fallen below threshold. $^{(b)}$ The notation "EC1–EC4" refer to the environmental constraints for the *minimum* carryover stock: (EC1) constant at 5.65hm^3, (EC2) constant at 11.30hm^3, (EC3) variable with 5% of the stock, (EC4) variable with 10% of the stock. $^{(c)}$ The "Benchmark" model refers to the case where there is no penalty threshold. $^{(d)}$ The notation "$\underline{Q}1 - \underline{Q}3$" refer to the threshold levels of the irrigation use that lead to $\{25\%, 20\%, 10\%\}$ of the land left fallow, respectively.

Table 4: **Lower Partial Moments for Irrigation Use in the Simulation**

		Shortfall Probability ($\kappa_2 = 0$)				Expected Shortfall[a] ($\kappa_2 = 1$)				Semivariance ($\kappa_2 = 2$)			
	Period	EC1[b]	EC2	EC3	EC4	EC1	EC2	EC3	EC4	EC1	EC2	EC3	EC4
$\underline{Q}1=109$[c]	5	0.68	0.58	0.49	0.30	40.74	33.87	26.60	12.35	2432	1998	1531	646
	10	0.31	0.36	0.37	0.44	18.54	20.03	19.43	16.76	1096	1157	1104	835
	15	0.26	0.33	0.35	0.43	15.24	18.86	18.90	17.10	908	1095	1081	877
	25	0.30	0.31	0.33	0.39	17.79	17.94	17.87	14.67	1067	1054	1028	738
	Overall[d]	0.34	0.35	0.36	0.42	20.51	20.01	19.42	15.90	1227	1168	1106	801
$\underline{Q}2=121$	5	0.91	0.73	0.68	0.51	10.91	9.34	8.03	3.95	400	373	292	72
	10	0.82	0.72	0.68	0.61	9.05	8.47	7.91	5.02	288	304	271	96
	15	0.74	0.69	0.69	0.64	8.38	7.56	7.32	5.23	277	239	222	93
	25	0.71	0.69	0.68	0.66	6.97	7.13	7.03	5.51	192	212	211	99
	Overall	0.67	0.67	0.68	0.71	6.84	6.75	6.51	5.86	197	188	163	101
$\underline{Q}3=152$	5	1.00[e]	1.00	1.00	1.00	19.12	20.32	20.45	20.85	1071	1206	1210	1186
	10	1.00	1.00	1.00	1.00	20.90	21.11	21.14	21.89	1223	1236	1237	1297
	15	1.00	1.00	1.00	1.00	21.13	21.04	21.00	21.26	1238	1219	1209	1232
	25	1.00	1.00	1.00	1.00	19.85	20.38	20.44	20.51	1064	1134	1136	1137
	Overall	1.00	1.00	1.00	1.00	19.61	19.87	19.89	20.41	1087	1110	1107	1140

Note: [(a)] Expected shortfall and semi-variance are measured in hm^3 and squared hm^3, respectively. [(b)] The notation "EC1–EC4" refer to the environmental constraints for the *minimum* carryover stock: (EC1) constant at $5.65hm^3$, (EC2) constant at $11.30hm^3$, (EC3) variable with 5% of the supply, (EC4) variable with 10% of the supply. [(c)] The notation "$\underline{Q}1$–$\underline{Q}3$" refer to the threshold levels of the irrigation use that lead to $\{25\%, 20\%, 10\%\}$ of the land left fallow, respectively. [(d)] The term "Average" indicates the average over all periods. [(e)] The probability value "1.00" does not imply certainty, but is due to rounding of the results.

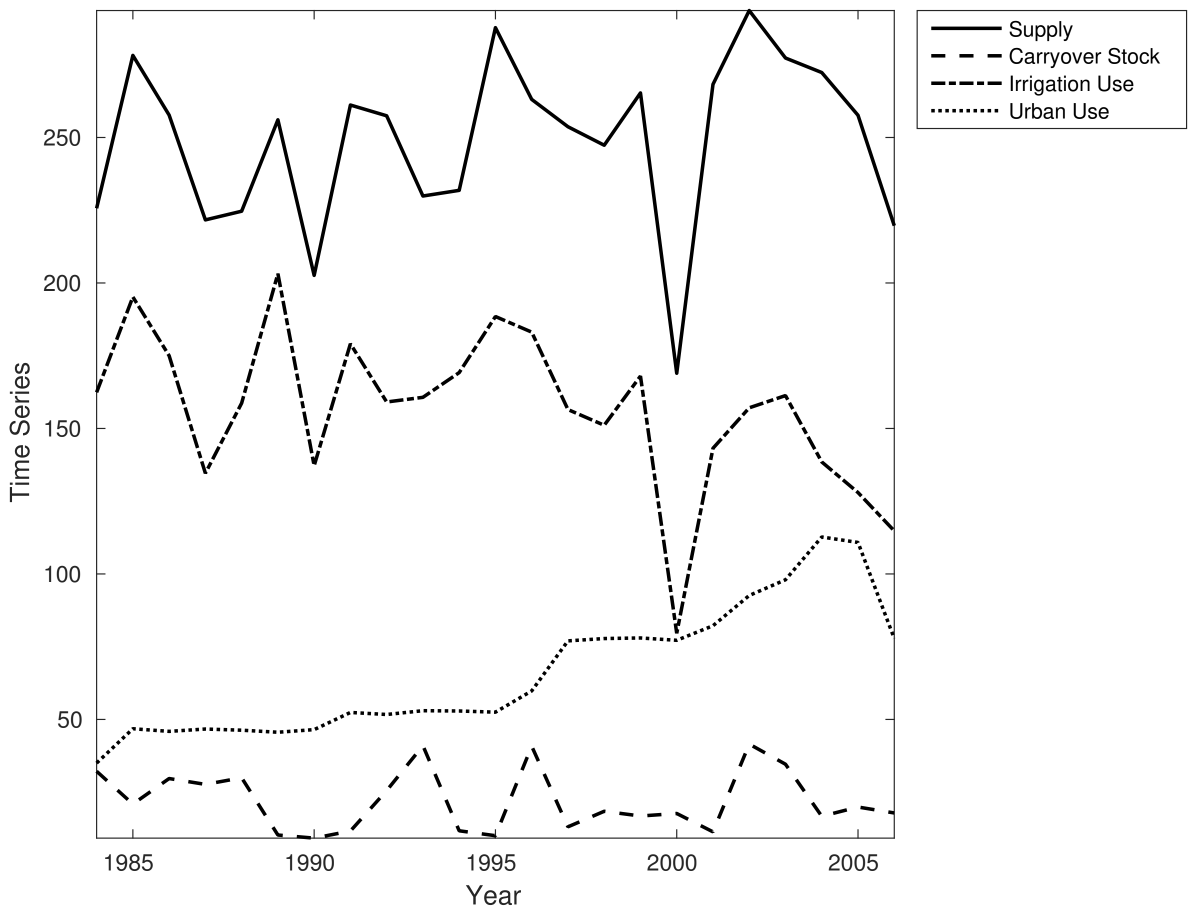

Figure 1: Annual flows in Kartalkaya Dam (year starting in October)

Note: In this figure, we observe that the fluctuations in the water supply affects the irrigation use more than the urban use. In fact, the urban use has steadily increased over time, thanks to the population growth, while shortages limit farmers' ability to access enough water from the reservoir.

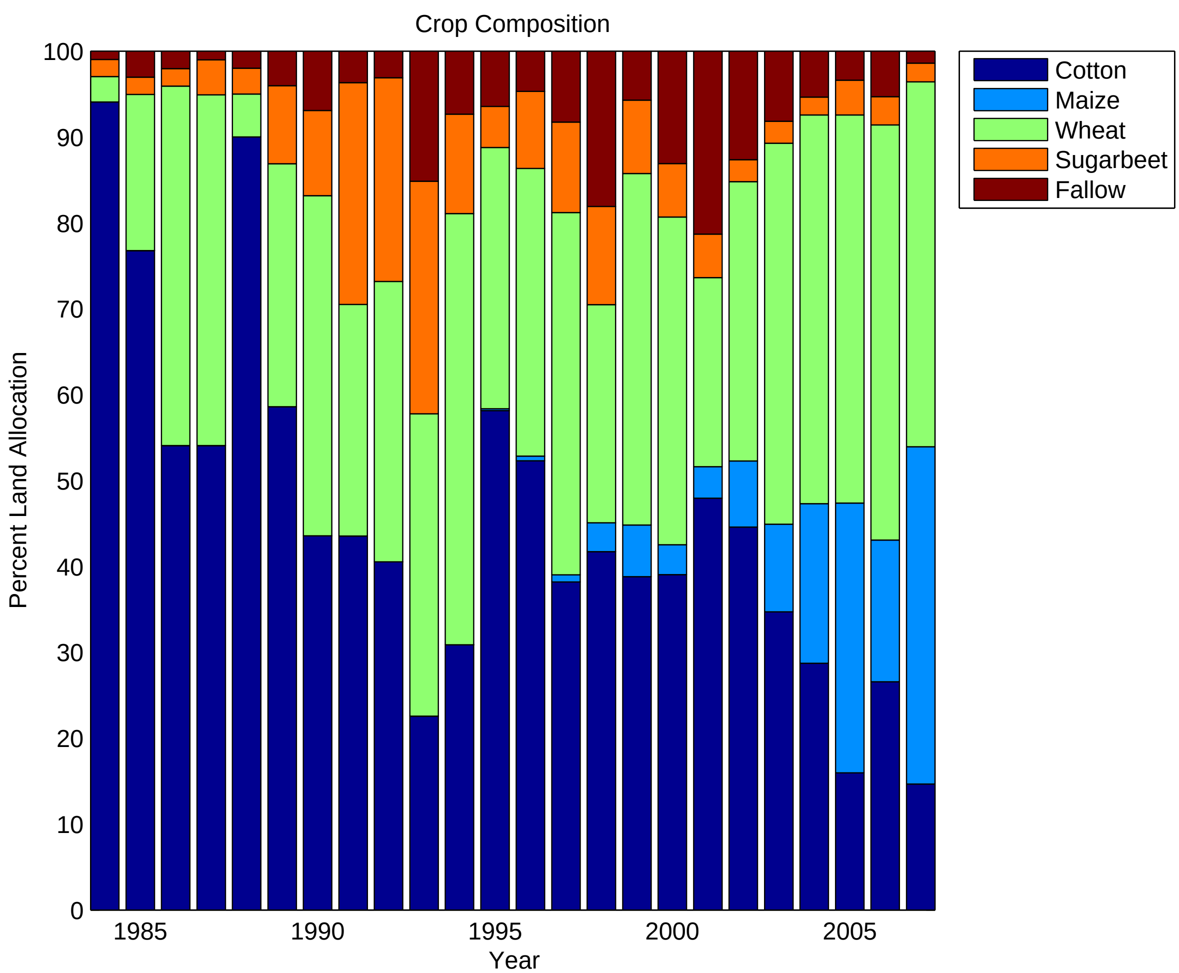

Figure 2: Changes in crop composition for the period 1984–2007

Note: In this figure, more than 90% of the land was initially allocated for cotton. Over time, this proportion has decreased considerably over time. Meanwhile, maize has emerged in late 1990s as a lucrative option for land allocation, due to increasing yields in seed quality and corn prices. Finally, the proportion of land left fallow has increased in late 1990s and early 2000s (it peaked at more than 20% in 2001), mostly due to the severe water shortages experienced in the region.

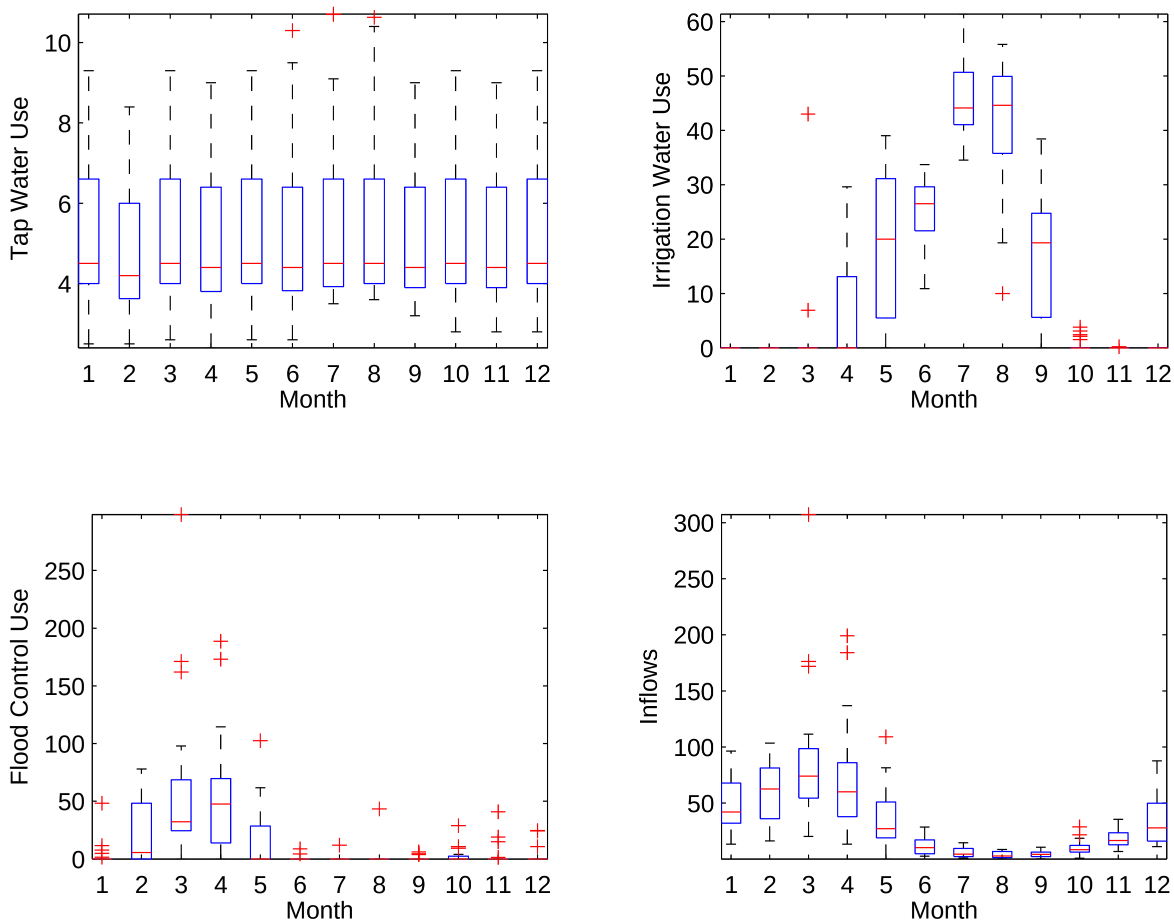

Figure 3: Boxplot of the reservoir flows (in hm^3)

Note: According to this figure, tap water use (on a monthly basis) has been steady (also illustrated in Figure 1). Meanwhile, irrigation use is highly seasonal, and reach to its peak levels during June and July, while inflows (and therefore release for flood control) drop to almost zero during the irrigation season.

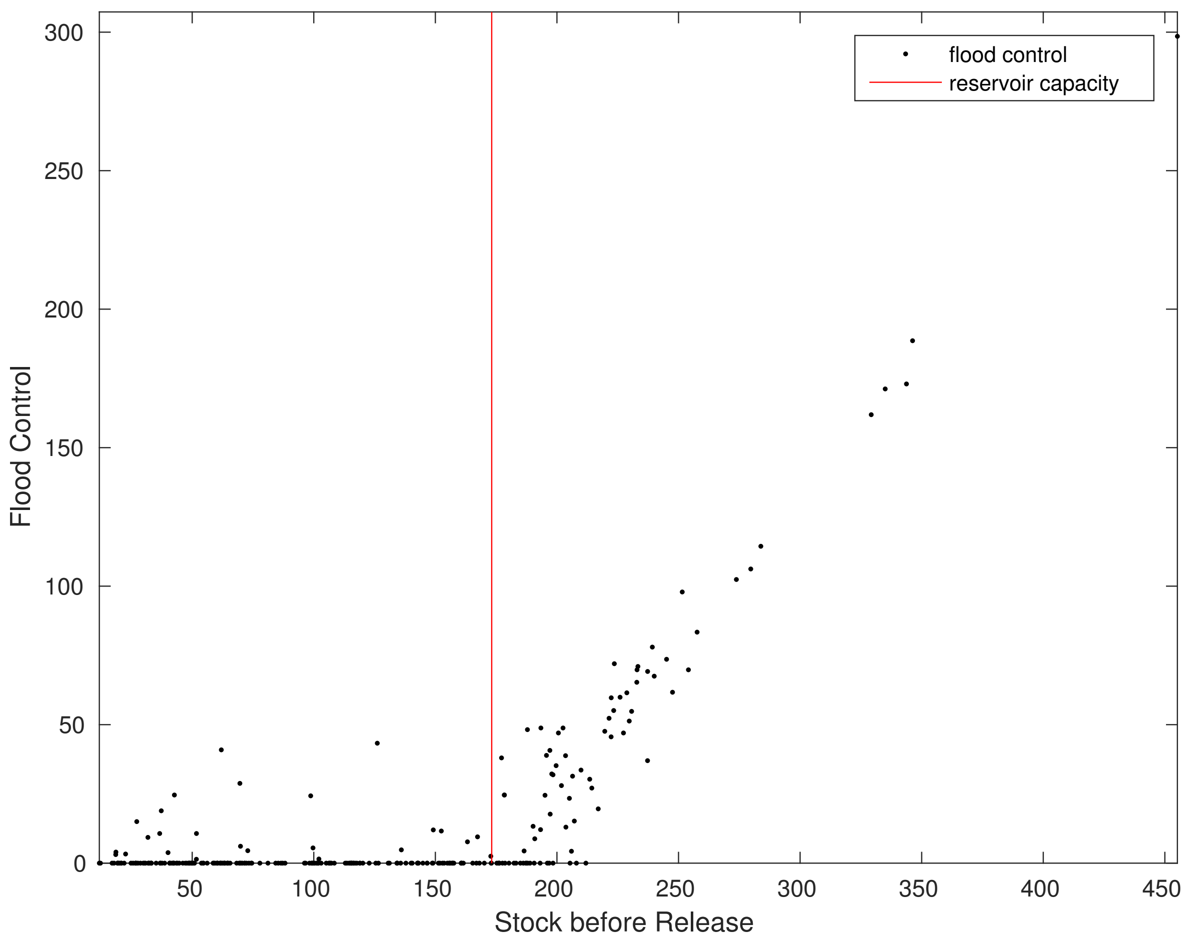

Figure 4: Water released to avoid overflows (in hm^3) versus total supply before release

Note: In this figure, the horizontal axis represents the total amount of water collected during a period. Since the reservoir capacity (indicated by the vertical line) is around $173hm^3$, any amount exceeding this threshold is released to avoid overflows, as illustrated on the vertical axis. This relationship suggests that the water release for flood control is censored from below, so a Tobit model would be a relevant model to fit the data. It is also worth noting that the *total supply* of water is the amount collected minus the release for flood control and is the net stock that is available for consumption and savings.