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DROUGHT RESILIENCE IN AGRICULTURE: THE ROLE OF TECHNOLOGICAL OPTIONS, LAND USE DYNAMICS, AND RISK PERCEPTION

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ABSTRACT. Sustained droughts coupled with increasing pressure from urbanization severely test the ability of farmers to continue in agriculture. Understanding farmers' resilience to such pressures is increasingly becoming a significant policy concern. In this paper, a new measure of resilience to severe and sustained droughts in agriculture is derived as the ability to continue farming by saving and carrying forward water through the adoption of water efficient technology. In addition, the role of behavioral factors—such as subjective risk perception over the probability of droughts, of the probability of land getting urbanized, and of resistance to revising beliefs over water scarcity situation—in determining farmers' resilience to droughts is explored. Findings highlight the key role played by behavioral factors in influencing the decision to adopt when the economic factors, such as the price of water, do not capture the true opportunity costs of water. The range of available technological options is found to be crucial too, as marginal improvements in technology do not encourage adoption. An empirical application to the case of lettuce farming in Western Australia reveals that in the presence of speculative benefits from land rezoning, technological adoption is done only for enhancing profits in agriculture and not for improving resilience to droughts. Land rezoning possibilities may further distort technology adoption decisions, thereby, reducing resilience to droughts.

KEY WORDS: Drought resilience model, risk perception, technology adoption model, water scarcity, land rezoning.

1. Introduction. Agriculture all over the world is facing pressure to use water efficiently due to increasing scarcity and rising urban and

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environmental water demands. When faced with the prospect of long-term water shortages in agriculture, farmers have the option of mitigating water scarcity through adjusting crop choices or through crop management, such as investment in water-saving options like drip irrigation, or to exit farming. Given these tough choices faced by the farmers, their persistence in agriculture, particularly in presence of sustained droughts, is becoming an important policy question that remains to be tackled adequately.

In this paper we model the problem of decision making under uncertainty relating to investment in water-saving technology for a farmer faced with long-term water scarcity and urbanization pressure. A measure of the farmer's resilience in agriculture is derived that is based upon the number of years of sustained droughts that he can withstand before exiting agriculture. Additionally, we explore the role of psychological influences such as belief revision and probability weighting on the decision to adopt water-saving technology that may impact a farmer's resilience.

Measuring farmers' resilience against severe droughts is an aspect that has not been fully explored in the literature to the best of the authors' knowledge.[1] Whereas several factors such as a preference for rural lifestyle choice or the ability to substitute agricultural income with other sources of income can make farmers resilient to droughts, in this paper we refer to resilience as pertaining to the ability of the farmer to continue farming despite decreasing water supply. Accordingly, resilience to sustained droughts could be enhanced through adoption of water-saving technology. Several factors may influence technology adoption. These could be economic, political, technological, or behavioral. Farmer heterogeneity, which may lead to differences in size, productivity, or over risk perceptions, may play a key role in deciding who adopts and who exits. Climatic and policy related variations in water supply are a crucial factor too, as they introduce uncertainty over returns from such investments in technology. Sunk cost in new technology and the possibility of speculative rewards from land rezoning could also be determinants in investment decisions. But the overall impact of each of these factors can be optimally evaluated only when explored simultaneously.

Most of the existing work on technology adoption (for instance, Khanna, Epohue, and Hornbaker [1999], Carey and Zilberman [2002], and Isik [2001]) is based upon the option value approach first taken by Dixit and Pindyck [1994] and McDonald and Seigel [1986]. This basically argues that irreversibility associated with the investment in sunk costs presents an option value for waiting and, therefore, delays investment. However, although the option value approach derives an important insight into the timing of adoption, which is not captured by the net present value approach, there are several other equally important factors that may influence technology adoption decisions by farmers, which have not been adequately dealt with in the literature. These include behavioral factors, such as risk perception over droughts, opportunity for speculative benefits from land rezoning, unavailability of economically viable technological options, and the political economy of agriculture. Although Carey and Zilberman [2002] find water markets as discouraging adoption in the United States, in Australia the price of water has been found to be too low to influence water-saving technological choices in agriculture (Brennan [2007]). Subjective perception of the probability of severe droughts may vary among farmers and over time. Such considerations as well as the possibility of reaping higher land prices from future urbanization make the prediction of technology adoption a complex exercise.

In this paper, we explore the nature of linkages between these previously unexplored factors and their impact on farmers' resilience to water scarcity, severe droughts, and pressure from urbanization. The approach involves modeling the farmers' ability to carry forward some or all of the water saved through better technology, which would have implications for their survival in the years when water supply is severely constrained through droughts. This ability to save water for the future makes their survival in the wake of a drought endogenous to their current decisions related to water abstractions and technology adoption.

In the remaining paper, we first lay out the analytical framework of the model of technology adoption decisions in the presence of a stochastic water supply, possibilities of land urbanization (which yields positive rewards), and severe droughts. Next, we illustrate the intuition through an application to the case of lettuce farming in Western Australia. Finally, the discussion and conclusion sections highlight and generalize the main findings.

2. Model. The model considers a farmer who has a single source of water that could be a reservoir that he privately maintains or an allocation from the government. The stock of water is annually augmented through rainfall. The stock dynamics of the reservoir follows:

$$\text{reservoir}(t+1) = \text{reservoir}(t) + (\text{rain}(t)) \cdot (1 - P(\text{drought})) - h(t), \tag{1}$$

where rain(t) follows a normal distribution with mean μ and standard deviation σ, and $h(t)$ is the water harvested by the farmer in each time period. Harvesting is optimally derived by the model. Further, P(drought) is the possibility of a per period severe drought in the wake of which there is no water allocation to the farmer (or there is no rainfall through which he could augment his reservoir) and the farmer has to rely entirely on the stock of existing reservoir for farming as long as the drought continues. Whenever a drought happens, he is assumed to harvest a fixed water quantity equal to "mets," which is the minimum evapotranspiration required for producing crops. The "mets" value is a proportion of optimum water application in a normal year, which is essential to avoid damage to the crops.[2] Thus, the reservoir in drought years takes the following path

$$\text{reservoir}(t+1) = \text{reservoir}(t) - \alpha \cdot \text{resevoir}(t) - \text{mets}, \tag{2}$$

where α is the proportional decrease in reservoir water due to evaporation, leakage, and so forth. We further assume, without any loss of generality, that there is no leakage from the reservoir in the wet years. Once the reservoir level goes below "mets," the farmer cannot sustain agriculture for another year and has to exit farming.[3] The number of consecutive years, $n(t)$, for which he can sustain in a severe drought depends on several factors including his reservoir level at time t at which consecutive droughts begin, on α and on mets. This value of n is crucial in determining the farmer's survival in agriculture and, therefore, could be construed as a measure of his resilience and is derived by solving equation (2) for fixed amounts of harvesting (mets) until there is less than mets amount of water left in the reservoir as[4]

$$n(t) = \text{ceil}\left\{ \frac{\log\left(\dfrac{(1+\alpha)\cdot \text{mets}}{\text{mets} + \alpha \cdot \text{reservoir } (t)}\right)}{\log(1-\alpha)} \right\}. \tag{3}$$

On exit from farming, he recovers some resale value (*resale*) of land, equipment, and so on. The farmer's exit from agriculture could also be induced by another event: rezoning of his farmland for urbanization. Urbanization gives him greater rewards for the same land (say U) as compared to a resale value of land that he receives from selling it before land is rezoned. The probability of land getting rezoned in any year "t" is assumed to follow a sigmoid function and is based upon the assumption that as population pressure increases, agricultural areas near the urban periphery get urbanized over time

$$P(L) = \frac{at}{b+t}, \tag{4}$$

where L refers to land rezoning and parameters a and b determine the maximum value and the time at which the probability of rezoning peaks. The profit function for the farmer in any normal year is given as

$$\text{rainprofit}(t) = \pi f(h) - c_h(t), \tag{5}$$

where π is the price of the agricultural produce, and $c_h(t)$ is the cost of harvesting water (or the price paid to the government for its allocation). In a severe drought year, as "harvest = mets," profit is defined as

$$\text{droughtprofit}(t) = \pi f(\text{mets}) - c_h(t). \tag{6}$$

Thus, the expected gain E_G from farming in any year is

$$E_G = \text{rainprofit}(t)\cdot(1 - P(\text{drought})) + \text{droughtprofit}\cdot P(\text{drought}). \tag{7}$$

Next, let us consider the future output of a farmer starting from a particular year. In order to obtain the total reward from farming, we break it into several possible cases that are independent of each other. Let us divide these cases on the basis of year T until the farmer practices normal farming and after which the exit situation manifests. Thus, for exactly T years, he gets his expected gain every year, and after that he must exit, either due to rezoning in $T+1$ or due to n consecutive droughts, from year $T+1$ to year $T+n$. This exit situation can occur in several ways. These are rezoning in year $T+1$ and no n consecutive droughts, rezoning in year $T+1$ and n consecutive droughts, and no rezoning in year $T+1$ and n consecutive droughts. The combined probability of this happening is

$$P(L) + (1 - P(L)) \cdot P(\text{drought})^{n(t)}. \tag{8}$$

Up to year T, the farmer obtains the expected gains from farming in each year. Therefore the profit from agriculture up to year T is

$$\text{agprofit}(T) = \{P(L) + (1 - P(L)) \cdot P(\text{drought})^{n(t)}\} \left\{ \sum_{t=1}^{T} E_G \cdot e^{-rt} \right\}. \tag{9}$$

Upon exit, rewards are either obtained due to exit from rezoning or losses from an n-year drought followed by a resale value of land and capital from exit in the year $T+n$. Thus expected exit rewards are

$$\begin{aligned} \text{exitprofit}(T) = {} & P(L)Ue^{-r(T+1)} + (1 - P(L)) \cdot P(\text{drought})^{n(T)} \\ & \times \left\{ \text{resale} \cdot e^{-r(T+n(t)+1)} + \sum_{t=T+1}^{T+n(t)} \text{droughtprofit}(t) \cdot e^{-rt} \right\}. \end{aligned} \tag{10}$$

The total profit (Eprofit) obtained from farming and exit, therefore, is the sum of equations (9) and (10) and given as

(11)

$$E\text{profit} = \int_0^{\infty} \left\{ \begin{array}{l} \left\{P(L) + (1-P(L)) \cdot P(\text{drought})^{n(t)}\right\} \\ \quad \cdot \left\{\sum_{t=1}^{T} E_G \cdot e^{-rt}\right\} + P(L) \cdot U \cdot e^{-r(T+1)} \\ +(1-P(L)) \cdot P(\text{drought})^{n(T)} \\ \quad \cdot \left\{\text{resale} \cdot e^{-r(T+n(t)+1)} + \sum_{t=T+1}^{T+n(t)} \text{droughtprofit}(t) \cdot e^{-rt}\right\} \end{array} \right\}.$$

So far we have not included the possibility for water-saving technological options. There is evidence in the literature of the influence of water shortages on technology adoption decisions. For instance, drip irrigation technology, even though it was first introduced in California in 1969, did not pick until 1977–1979. This coincided with severe droughts in the region and higher oil prices (Carey and Zilberman [2002]). The impact of droughts on inducing technology adoption has also been studied by Zilberman et al. [1995]. Shuchk, Frasier, Webb, Ellingson, and Umberger [2005], using survey data for adoption of efficient irrigation technology in drought-affected regions of Colorado, find that drought indeed significantly improves the percentage of farms adopting modern irrigation technologies, with the farmers having the most reliable sources of water as the major adopters. A crucial question then is how the technology adoption decision is influenced when the water savings resulting from such an adoption could be used for enhancing resilience against sustained droughts.

The farmer may have a choice to adopt a water-saving technology that reduces his water application rates and allows him to sustain through longer drought periods. More efficient technologies may allow the farmer to survive through drought periods by reducing water applications to minimum possible levels (Schuck et al. [2005]). However, this comes at a sunk cost equal to the price of the new technology, which is irreversible. Therefore, he is faced with a binary choice over whether or not to adopt.

Let the cost of adoption be "ctech" and the choice of adoption be 1 when adopted and 0 when not adopted. The new "rainprofit" function is derived as[5]

(12)

$$\begin{aligned}
&\text{rainprofit}(t)\\
&\quad = \{\pi \cdot f(h) - c_h(t)\} \cdot (1 - x(t) \cdot (1 - xdot(t)) \qquad \Lambda \text{ till adoption}\\
&\qquad + \{\pi \cdot f^{\text{new}}(h) - c_h(t) - \text{ctech}\} \cdot x(t) \cdot xdot(t)\\
&\qquad\qquad \Lambda \text{ for the first year of adoption}\\
&\qquad + \{\pi \cdot f^{\text{new}}(h) - c_h(t)\} \qquad \Lambda \text{ after adoption,}\\
&\qquad \text{where } xdot(t) = x(t) - x(t-1).
\end{aligned}$$

Similarly, "droughtprofit" is obtained as

(13)

$$\begin{aligned}
&\text{droughtprofit}(t)\\
&\quad = \{\pi \cdot f(\text{mets}) - c_h(t)\} \cdot (1 - x(t) \cdot (1 - xdot(t)) \qquad \Lambda \text{ till adoption}\\
&\qquad + \{\pi \cdot f^{\text{new}}(\text{mets}) - c_h(t) - \text{ctech}\} \cdot x(t) \cdot xdot(t)\\
&\qquad\qquad \Lambda \text{ for the first year of adoption}\\
&\qquad + \{\pi \cdot f^{\text{new}}(\text{mets}) - c_h(t)\} \qquad \Lambda \text{ after adoption,}\\
&\qquad \text{where } xdot(t) = x(t) - x(t-1).
\end{aligned}$$

The model so far does not consider the behavioral aspects of decision making in agriculture when faced with severe droughts. The behavioral element of our model is based on accumulated evidence in economics and psychology literature (see summary in Hurley and Shogren [2005]). Assume that the farmer assigns higher weights to low probabilities of droughts and lower weights to high probabilities of droughts (also see Starmer [2000] and Ranjan and Shogren 2006). Let the weighting function follow an inverse S-shape. Following Prelec [1998], we use a two-parameter weighting function as

$$w(p) = e^{-\theta \cdot (-\ln p)^{\gamma}}, \tag{14}$$

where θ is the parameter that primarily determines elevation, and γ is the parameter that primarily determines curvature. *Elevation* reflects the inflection (reference) point at which the farmer switches from over-estimating low probability events to underestimating high probability events, that is, the degree of over- and underestimation. *Curvature*

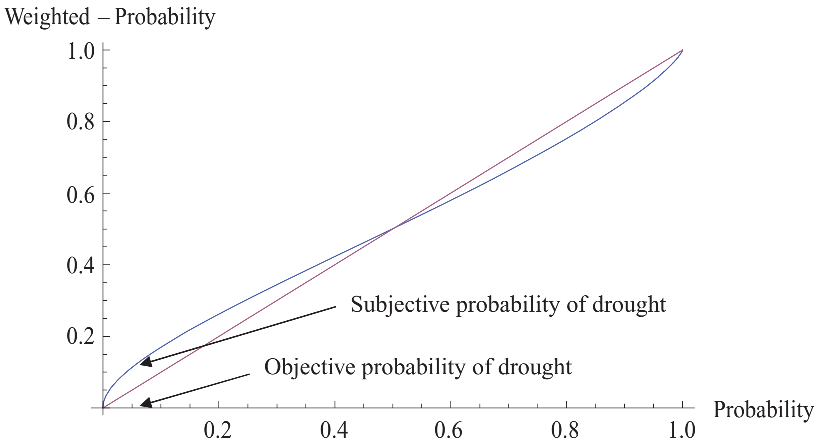


FIGURE 1. Subjective weighting of the probability of a drought.

captures the idea that the farmer become less sensitive to changes in probability the further they are from the inflection point (Tversky and Kahneman [1992] and Gonzalez and Wu [1999]). Figure 1 subsequently shows the subjective weighting of the probability of droughts that converts an objective probability of once in 20 years (which roughly reflects the drought frequency in Australia, Bureau of Meteorology [2008]) drought into a subjective probability of once in 10 years drought.

Further, so far we have assumed that per period additions to the reservoir, either due to rainfall or due to allocation, are given by a distribution with a certain mean and variance. However, when water scarcity is climate change related, it is more likely that the mean rainfall (and therefore the water allocation) would be downwardly adjusted over time. Rainfall is assumed to come from a distribution, the mean of which gets adjusted over time as

(15)
$$\text{new\_mean} = \frac{[\text{wt\_prior\_mean} \cdot \text{prior\_mean}] + [\text{wt\_prior\_yr} \cdot \text{prior\_yr}]}{(\text{wt\_prior\_mean} + \text{wt\_prior\_yr})},$$

where "prior_mean" is the mean rainfall up to the penultimate year, "wt_prior_mean" is the weightage assigned to the mean rainfall up to the penultimate year, "prior_yr" is the rainfall of preceding year, and "wt_prior_yr" is the weightage assigned to rainfall of preceding year. Given the above characterization of the farmer's problem, his task is to select optimal water allocation rate and decide whether or not to adopt the water efficient technology in order to maximize his profits. Note that if the rewards from land rezoning are very high or the profits from farming very low (when the price of water may become large), the farmer's objective may not be to maximize his stay in agriculture any more. The measure of his resilience to droughts, as given by the parameter n, may still indicate the length of drought that he can endure before exiting. In order to further explore how these different aspects influence his decision making, we provide an empirical illustration of the above analytical model that best fits the above characterization. We pick the case of lettuce farmers in Western Australia, who are faced with the prospect of water curtailment in future due to declining groundwater levels and increasing water demand from the urban and environmental sectors.

3. Empirical illustration. We consider a lettuce farmer in Western Australia, who may be faced with water restrictions in future. The Appendix presents the parameters used for the base case simulations. Currently, most of the water in Western Australia is derived from the Gnangara Mound, which is a large underground reservoir for water (Department of Environment [2005]). Historically, the Mound was considered as an unlimited source of water, but with increasing frequency of droughts, the water levels have been declining. Declining ground water levels have adversely affected the groundwater dependent ecosystems over time. Additionally, the city of Perth in Western Australia is the largest consumer of this underground water and has been making increasing demands on this resource from a mining boom related population explosion. Current policy options for mitigating water scarcity involve metering water use in agriculture and curtailing its allocation to farmers (Brennan [2007]).

Given this brief background, assume that the farmer receives an annual water allocation from the government, a proportion of which he

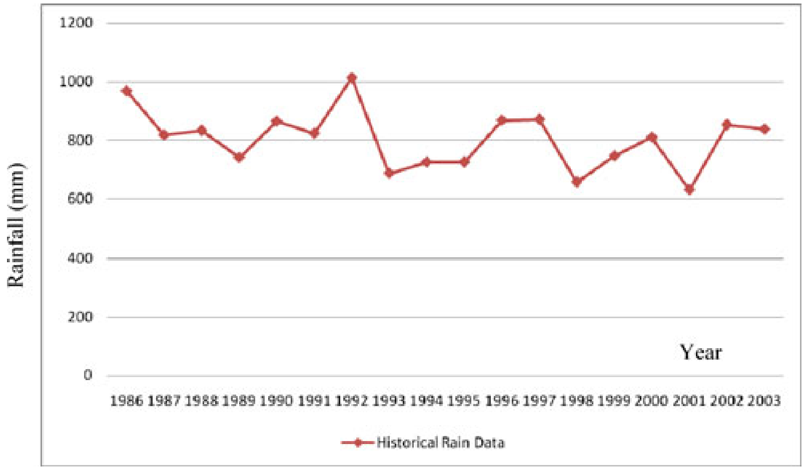


FIGURE 2. Historical annual rainfall in mm (Xu et al. [2005]).

can carry over to the next year. Assuming he has no other sources of water, his water reservoir stock would evolve as

(16)
$$\text{reservoir}(t+1) = \beta \cdot \text{reservoir}(t) + \text{rainadj} \cdot \text{allocation}(t) - h(t),$$

where "rainadj" is a curtailment from his current allocation. It is assumed that the government does not allocate any water during a drought year. Water allocation is based upon the realized rainfall in each year. For instance, if rainfall is 600 mm, it amounts to 6 megaliters (ML) of water per hectare for the farmer. Figure 2 subsequently depicts the rainfall in the past 18 years, which has a mean and variance of 8.038 and 1.0082, respectively.

The gross revenue function in lettuce farming is based upon Brennan [2007] and is calibrated as

(17)
$$\chi \cdot (\vartheta - exp(-\eta - \kappa \cdot h(t))) - \varsigma \cdot \exp(-\varepsilon \cdot h(t)) + \tau \cdot (\varphi - \delta \cdot h(t)^2),$$

where harvesting of water for farming is in ML and χ, ϑ, η, κ, ς, ε, τ, φ and δ are parameters of the production function and are detailed

TABLE 1. Lettuce production function estimates for 60% and 90% DU.

Parameters	Parameter values (60% DU)	Parameter values (90% DU)
η	−1.95	−1.63
χ	10,000	27,500
κ	0.86	1.24
ϑ	0.88	0.355
ς	4620	5580
τ	2.8	12.4
φ	7	9.8
δ	4.8	1.1
ε	0.044	0.038

Note: Aforementioned table shows parameter values selected for two technological options available to the farmers. Parameter values used for the calibration of the gross margin function for the technology with 60% DU are shown in column 2 and for the technology with 90% DU are shown in column 3.

in Table 1. These parameters are calibrated to mimic declining gross revenue based upon empirical evidence.

In the aforementioned equation, the first term $\chi \cdot (\vartheta - \exp(-\eta - \kappa \cdot h\ (t))$ when considered alone ensures that the gross margin plateaus as harvesting increases; however, when considered together with the last term $\tau \cdot (\varphi - \delta \cdot h(t)^2)$ it leads to a decline in productivity as water application exceeds a certain optimal level. The middle term $\varsigma \cdot \exp(-\ \varepsilon \cdot h(t))$ is an adjustment factor that helps calibrate the production function to the observed data. The assumption related to a decline in productivity is consistent with the empirical evidence in lettuce farming, which is caused by nitrogen leaching. The gross revenue functions for the two sprinkler irrigation technologies are presented in Figure 3. This function is inclusive of the cost of water, which is \$50/ML.

Sprinklers with 60% and 90% distribution uniformity (DU) are considered as two widely available technological options, though intermediary uniformity is also possible. Increase in the DU allows for more efficient use of water. The farmer is assumed to have 60% uniformity

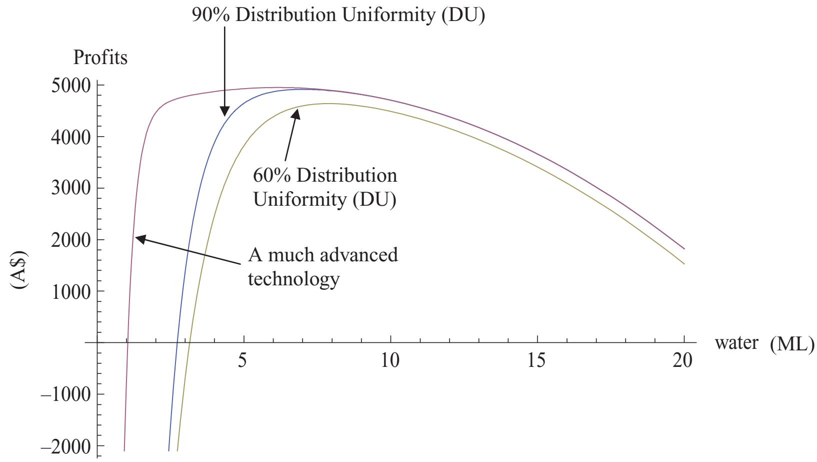


FIGURE 3. Production function for lettuce under 60 and 90% DU and under a much better technology possible in future.

for the base case. The technology with 90% DU comes at an additional cost of about $8,165 per hectare, which may not be reverted back to after investment.

3.1 Scenario description. In the base case scenario, we assume that the farmer has a prediction over future water supply that is based upon the mean and variance of past 18 years of rainfall. This data was shown in Figure 2 previously. The predictions are generated using a random number generator in GAMS for the mean and variances based upon the empirical observation.

Short-term forecasts play a relatively minor role in the decision making of farmers as compared to medium and long-term forecasts. Therefore, the pattern generated by the random predictions could be considered as one possible long-term scenario under consideration by the farmer, while he derives his long-term optimization path. The farmer revises his expectation over the mean rainfall in each period as given by equation (15) previously. In the base case the farmer does not adopt the water saving technology, as there is enough rainfall in each year. The year in which technology is adopted is presented in Table 2.

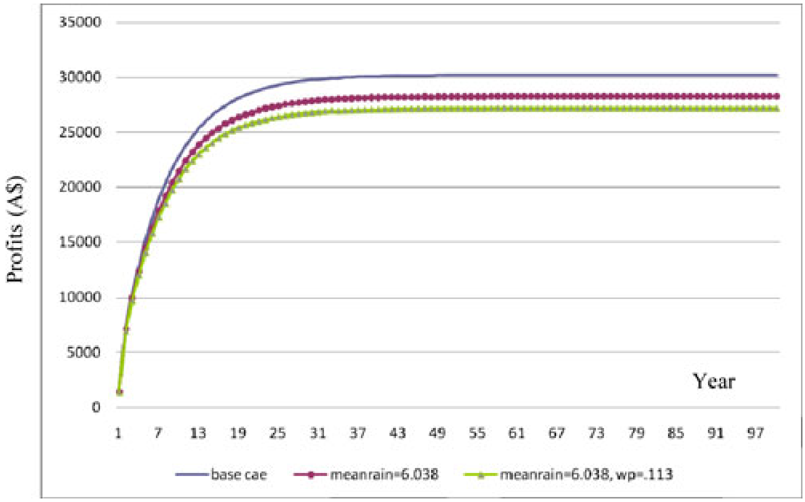
TABLE 2. Year of water saving technology adoption.

Scenarios	Scenario description	Year of adoption
Base case		No adoption
1 ($\mu = 6.038$)	Reduced expectation of future rainfall	48
2 ($\mu = 6.038$, weighted risk of drought)	Increase in perceived risk of droughts to one in 10 years	34
3 ($a = 0.8$, $b = 0.5$)	Higher probability of land rezoning	48
4 ($\mu = 6.038$, no mean revision)	No revision of mean rainfall based upon new evidence	No adoption
5 (90% rainadj)	Water curtailment by policy maker	13
6 (initial reservoir = 15 ML)	High reservoir capacity	No adoption

Also note that we restrict the reservoir capacity (or carry forward capacity) to 5 ML of water. The number of years that a farmer could survive in the wake of a severe drought, as given by n, goes to zero right after the first year. This indicates that the farmer stays in farming only dependent upon the rainfall and will be out of farming as soon as the drought period starts. The expected profits from being in agriculture summed up to time t (as given by the variable "agprofit") are shown in Figure 4.

Water abstraction, rainfall, and the reservoir levels are depicted in Figure 5.

Next, we consider six variations from the base case that mimic various possibilities associated with farmer heterogeneity, policy interventions, reservoir capacity, and land rezoning probability. Scenario 1 studies the impact of a pessimistic expectation of future rainfall. In Scenario 2, we bring in risk weighting by augmenting the subjective risks



Note: A 200-year time horizon is selected in GAMS for numerical simulations, which mimics an infinitely lived farmer. Results are depicted for the first hundred years for ease of presentation here.

FIGURE 4. Expected agricultural profits until exit from farming.

associated with droughts. In the third scenario, the impact of a higher probability of urbanization on technology adoption is explored. In the fourth scenario we consider the case of a farmer who exhibits resilience or inertia in revising his expectations of future rainfall based upon current observations. In the fifth scenario the impact of policy intervention through water curtailment is simulated. Finally, in the sixth scenario the reservoir capacity is increased to allow for more water storage and carryover to the next period.

3.2 Simulation results. Table 2 depicts the key results from the scenario runs. In the first scenario, we lower the mean rainfall to 6.038 from 8.038 in order to observe the impact of an expectation of reduced rainfall on farmer's decision. The farmer adopts the technology in year 48. However, when the parameter c, which influences the gross revenue function, in the 90% DU case is changed to 3.3, adoption happens much earlier—in time period 20. This highlights the role of availability of technological choices in influencing technology adoption. Marginal

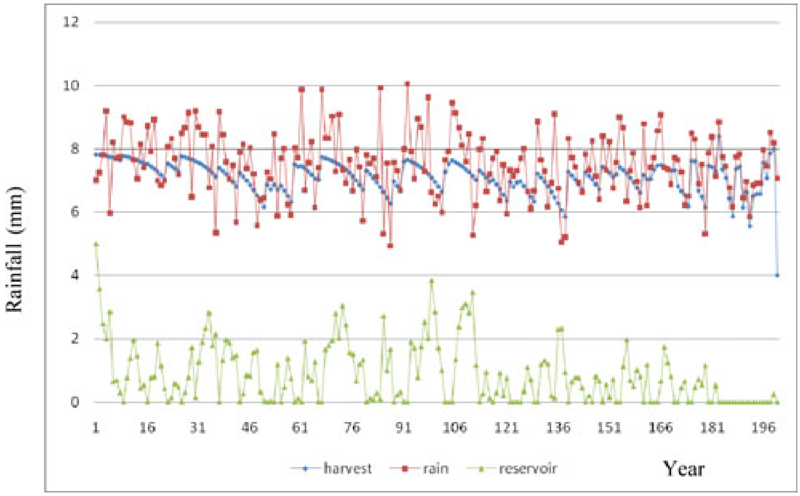


FIGURE 5. Rainfall, water abstraction, and reservoir levels under the base case.

improvements in technology discourage adoption as the costs of adoption are too high and can only be profitably incurred when adoption happens too far in future—when its discounted cost is lower. Note that the decision to adopt at any time is based upon intertemporal cost-benefit considerations. Therefore, it is cheaper to postpone costly investments for future.

In the second scenario, we consider the role of a farmer's subjective risk perceptions over the probability of severe droughts in future in influencing adoption. The base case has a 1 in 20 year chance of severe drought. However, the subjective weighing of the risks increases this chance to 0.11, that is, one in 10 years. The impact of this weighing is that technology adoption happens much earlier, in year 34.

In the third scenario, we consider the impact of a higher land rezoning possibility on technology adoption, keeping mean rain low at 6.038. This is achieved by raising the parameter a to 0.8, which increases the upper bound of maximum probability to 0.8. Surprisingly, this case leads to adoption in year 48, similar to the base case. This happens due to the exogenous nature of risk of rezoning and the associated positive rewards from rezoning that do not encourage water saving. It

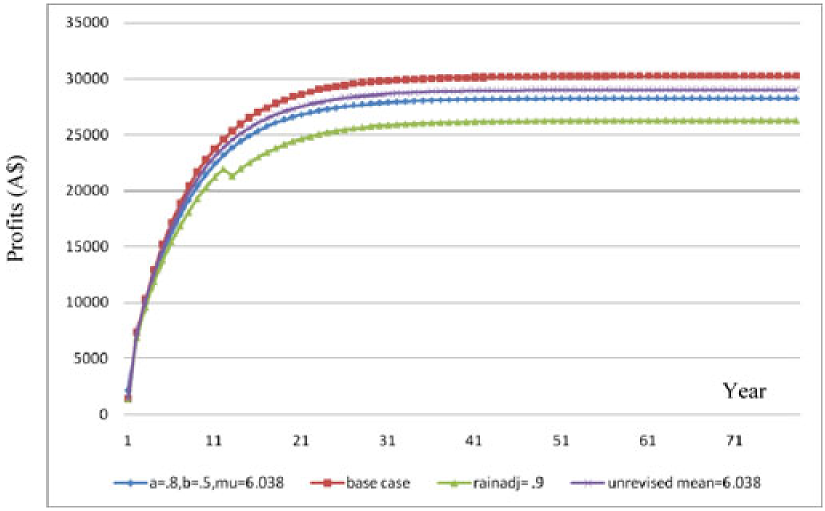


FIGURE 6. Expected agricultural profits until exit from farming.

is, however, possible that when urbanization comes at a cost, water saving options are encouraged. This result is consistent with an earlier finding in the literature, called "impermanence syndrome" (Lockeretz [1989]), that attributes inefficient farming to speculative rewards from land rezoning (Figure 6).

In the fourth scenario, we do not allow for revision of mean rainfall based upon current rain data, keeping the mean rain at 6.038. The idea is that this case is typical of a farmer who is averse to revising his beliefs and exhibits inertia or resilience in adapting to the changing climate. This case leads to no adoption compared to the case when revisions are allowed.

Revision of the mean rainfall could lead to lower future predictions if current rainfall is lower, which reduces the mean. If the first couple of years lead to a lower rainfall, the mean becomes lower than the unrevised mean case, and the future forecasts are bound to be lower.

Figure 7 depicts the rainfalls under revised and unrevised means. Note that the revised mean leads to under emphasis on more positive rainfall outcomes and over emphasis on the pessimistic outcomes.

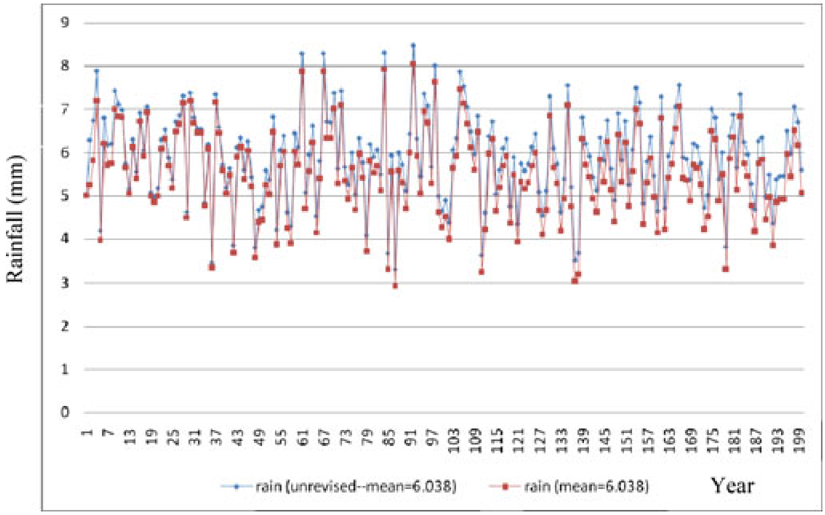


FIGURE 7. Rainfall under revised and unrevised means.

This leads to lower expected "agprofits" in the revised mean case as shown in Figure 8.

However, if the first couple of years lead to a higher rainfall, the opposite situation is possible as well—projected rain in future would be higher than the unrevised case. Therefore, when farmers consistently update their beliefs over future rainfall, they are prone to be resilient to drought or exiting earlier, depending upon the current rainfall situation.

In the fifth scenario, we consider the impact of a curtailment of the water supply by the policy maker. This situation may arise despite a good rainfall scenario as urban and environmental demand for water are given precedence. In this case we lower the water supply by 10% through the "rainadj" parameter ("rainadj" = 0.9). In this case technology adoption happens in the 13th year. In the final scenario, we consider the impact of a higher reservoir capacity on the farmer's decision to adopt technology. Not surprisingly, there is no technology adoption.

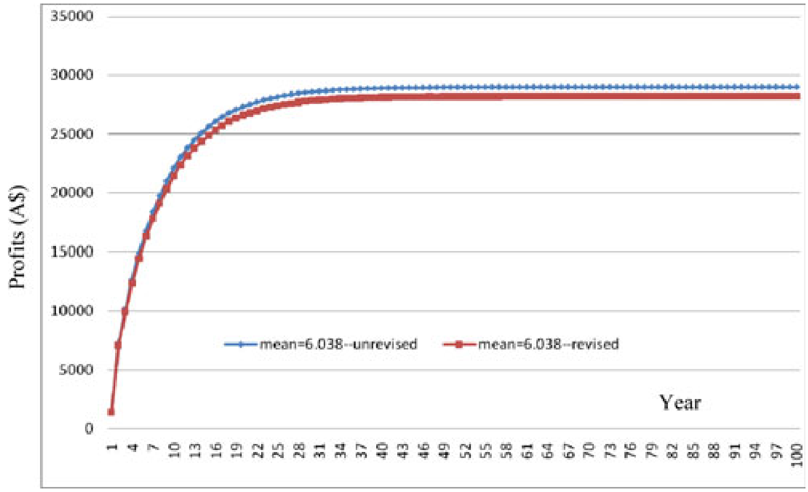


FIGURE 8. Expected agricultural profits until exit under revised and unrevised means for rainfall.

4. Discussion. The fact that the base case scenario does not lead to technology adoption is due to the expectation of an optimistic future rainfall scenario. Even though the farmers revise their means, the random realizations are still based upon a distribution with a high mean rainfall. The first scenario corrects for this over optimism by reducing the mean rainfall. Technology adoption happens but too far in future. This is because the future costs of technology adoption occurring far in future are low when considered in their present value terms. When a farmer incorporates intertemporal considerations in his decision making, future costs are discounted, thereby making it more attractive to postpone costly expenditures until later on in future. The sunk cost of capital discourages early adoption when the gains in water saving are not high.

When the possibility of much better technology exists, adoption happens much earlier as the benefits from water saving overrides the high costs of capital. Expectation of the possibility of severe droughts is equally important as it reduces the time to technology adoption when the risk of droughts is over weighted. Over weighting of risks has been found to be prevalent in the literature and is more likely to be the norm than the exception. However, the extent of over weighting may vary with population heterogeneity. A heterogeneous farming population would imply that technology adoption happens gradually among farmers, which in itself may have an added psychological influence over further technology adoption by the rest of the population. This phenomenon has been termed as "popularity weighting" in the literature (Ellision and Feudenberg [1993]). Another important consideration is the possibility of land urbanization in the future, which yields much higher returns to the farmers than from staying in agriculture. This could significantly influence the decision to adopt the technology when the land may be urbanized in future with a high probability. The results show that even when water is scarce, the possibility of land rezoning discourages adoption. The fourth scenario takes the case of a farmer that does not adjust his expectations over future rainfall based upon current observations. This case is interesting as it highlights the possibility of both positive and negative outcomes in terms of adoption, depending upon the present rainfall scenario. When water allocation is curtailed, technology adoption happens earliest of all the cases. This is an important outcome as it highlights the possibility of policy intervention in influencing adoption. On one hand, the ability to carry forward water encourages adoption, whereas on the other, a higher allocation of water discourages adoption. A combination of the two choices could be used to induce desirable levels of adoption by farmers. Finally, a higher reservoir capacity neither leads to technology adoption nor enhances resilience (by making n positive).

Most of the scenarios give a zero value for the resilience parameter "n" right from the very beginning. This is because of low rainfall and low starting levels of reservoir. In cases where reservoir capacity may be high, it does not necessarily imply that resilience would be higher either. The prospects of higher land value from urbanization do not provide any incentives to save water. Technology adoption occurs only for maximizing profits in agriculture, it is not done with the purpose of enhancing resilience. It is likely that when the social costs associated with exit from farming (such as loss of an agricultural lifestyle) are an important consideration for the farmers, farmers would be more inclined to adopt technology for enhancing resilience. Similarly, when droughts might adversely affect the value of land and are so severe that even the urban demand for agricultural land goes down, farmers may have a higher incentive to stay in agriculture and adopt measures that build their resilience in the wake of repeated droughts.

Finally, introduction of water markets could induce efficient technology adoption by raising the price of water, but unless the price is significant, there may not be enough incentive to adopt the technology with higher DU. For instance, Brennan [2007] finds that when water prices are raised to \$200/ML from their base case of \$50/ML, a farmer with 55% DU reduces his water application by 20%. Only when the added benefits from water savings exceed the cost of capital will the better technology be adopted. This is confirmed in our empirical exercise by raising the price of water to \$200/ML, which does not lead to adoption of the better technology. Other studies as well have found little private economic incentives for adoption geared towards enhancing resilience and have advocated for government subsidies instead (Thomas et al. [2007]).

5. Conclusion. In this paper we developed an economic model of decision making under uncertainty for a farmer faced with long-term water scarcity and urbanization pressure. A formula for farmer's resilience was developed that measured his ability to survive long-term droughts. Further, we derived the role of technological options in determining the resilience of farmers to sustained droughts. Several insights have emerged out of the analysis. First, risk perception influences technology adoption choices, thereby affecting farmers' ability to continue in farming when faced with the prospect of long-term droughts. Further, technological options that lead to marginal improvements in water saving are not availed of by farmers. Second, heterogeneity among farmers may determine who adopts and who does not. A farmer's ability to revise expectations over future water scarcity based upon current and past observations plays a crucial role in technology adoption. A farmer that does not revise his expectations of the mean rainfall based upon past and current observations will overestimate the mean rainfall in an approaching drought scenario and therefore may not adopt the technology. Third, land rezoning possibilities further distort the choice over technology adoption and may make farmers less resilient to droughts. Finally, economic factors such as the sunk costs of capital or water prices are the least important in influencing adoption when the new technology does not offer significant gains in water saving or when water prices do not capture the true opportunity cost of water. Yet, command and control options such as water allocation and the ability to carry forward water turned out to be highly effective in influencing technology adoption.

There is a further need to explore social and behavioral influences that may determine resilience in agriculture. Behavioral factors such as probability weighting and belief revisions may have a significant influence on technology adoption, as the results have pointed out. Yet, our understanding of such aspects is limited. An enhanced understanding of such influences would help accurately predict farmers' resilience in agriculture. A farmer's actions may also be influenced by the decisions of the neighboring farmers, through a learning effect as has been observed in the literature. Finally, understanding the nature of uncertainty related to future water availability is also important for policy purposes. This uncertainty could be either climatic (over which farmers have limited control) or could be policy related.

APPENDIX: DERIVATION of n

Here, we provide the methodology for the derivation of the value of n. At the end of the first year, reservoir dynamics is given as

$$\text{reservoir}(t+1) = \text{reservoir}(t) \cdot (1-\alpha) - \text{mets}.$$

At the end of the second year

$$\begin{aligned}\text{reservoir}(t+2) &= \text{reservoir}(t+1) \cdot (1-\alpha) - \text{mets} \\ &= \text{reservoir(t)} \cdot (1-\alpha)^2 - \text{mets} \cdot ((1-\alpha)+1).\end{aligned}$$

At the end of the nth year

$$\begin{aligned}\text{reservoir}(t+n) = {}& \text{reservoir}(t) \cdot (1-\alpha)^n \\ & - \text{mets} \cdot ((1-\alpha)^{n-1} + \Lambda + (1-\alpha) + 1).\end{aligned}$$

Using the formula for a geometric series

$$(1-\alpha)^{n-1} + \Lambda + (1-\alpha) + 1 = \frac{[1-(1-\alpha)^{n-1}]}{[1-(1-\alpha)]}.$$

Therefore,

$$\begin{aligned}&\text{reservoir}(t+n)\\&\quad=\text{reservoir}(t)\cdot(1-\alpha)^n-\text{mets}\cdot\left(\frac{[1-(1-\alpha)^{n-1}]}{[1-(1-\alpha)]}\right)=\text{mets}.\end{aligned}$$

Now, we consider a point where mets becomes equal to a reservoir level at year $(t+n)$. When the aforementioned equation is solved for using Mathematica, we get

$$n(t)=\left\{\frac{\log\left(\dfrac{(1+\alpha)\cdot\text{mets}}{\text{mets}+\alpha\cdot\text{reservoir}(t)}\right)}{\log(1-\alpha)}\right\}.$$

The next integer larger or equal to this value will have the reservoir level reduced to a level where there is no sufficient water to sustain agriculture for yet another severe drought (Table A). Hence the ceiling function is used. This finally gives equation (3).

TABLE A. Base case parameter values.

Parameter	Definition	Value	Units
A	Scaling parameter for rezoning probability	0.5	Scalar
B	Scaling parameter for rezoning probability	0.5	Scalar
μ	Mean for rainfall*	8.038	ML
σ	Standard deviation for rainfall	1.0082	ML
α	Proportional decrease of reservoir due to evaporation and leakage	0.05	Scalar

TABLE A. Continued.

Parameter	Definition	Value	Units
Mets	Minimum water application required during severe drought conditions to avoid extensive crop damage	4	ML
P	The probability of a severe drought where the rainfall goes below $\mu - 3\sigma$	0.05	Scalar
Resale	The value recovered from selling land and capital after exit from farming	100,000	Dollars per hectare
U	Value of land from urbanization	500,000	Dollars per hectare
θ	Scaling parameter for the inverted S-shaped weighing function	0.922	Scalar
γ	Scaling parameter for the inverted S-shaped weighing function	0.784	Scalar
wt_prior_year	Weightage given to rainfall of the preceding year	1	Scalar
wt_prior_mean	Weightage given to the mean rainfall of all the years up to the penultimate year	$(t - 2)$	Scalar
β	Proportion of water that can be carried forward		Scalar
Rainadj	Water curtailment parameter	1	Scalar
Ctech	Cost of capital	8165 per hectare	Dollars

*This the historical mean, which gets revised with new rainfall data.

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ENDNOTES

1. Conventionally, resilience has been defined in two ways in the literature. The first, termed as the "engineering resilience," defines it as the speed of bouncing back of any perturbed system (Pimm [1984]). The other, termed the "ecological resilience," is about the amount of stress that the system can tolerate before flipping from its original state to another stable but degraded state (Holling [1995], Carpenter and Cottingham [1997]). Other measures exist as well. Keil, Zeller, Wida, Sanim, and Birner [2008] derive a measure of drought resilience based upon reduction in consumption of basic household necessities. This study is based upon ENSO related droughts in central Sulawesi, Indonesia.

2. The mets value for rice is 80%; for fruits, vegetables and other crops is 60%; and for beef, dairy, sheep, and oilseeds is 40% (Quereshi, Connor, Kirby, and Mainuddin [2007]).

3. In reality, a farmer may continue in agriculture despite the depletion of the reservoir due to noneconomic benefits associated with farming such as rural lifestyle choices. Psychological factors such as optimistic expectations over future water scenarios may also delay exit. Incorporating noneconomic benefits is beyond the scope of this paper; however, this implies that our model tends to underestimate farmers' drought resilience.

4. This can be derived as shown in the Appendix.

5. Technically, the farmer can dis-adopt, but numerically a constraint can be imposed upon the model to disallow dis-adoption.

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