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Hurry up or wait: The effect of climate change and variability on the timing of private adaptation

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Abstract: Climate variability makes the future benefits of adaptation uncertain. When adaptation comes in the form of discrete investments that are difficult to adjust, this uncertainty creates an economic value (an option value) to delaying adaptation to collect more information. This option value suggests adaptation will be slower than predicted by benefit-cost analysis. However, it is unclear how increases in climate variability influence this adaptation option value. Addressing this knowledge gap becomes critically important since climate change in many areas will be characterized by temperature and precipitation that is more variable than historic conditions. This study uses down-scaled results from four different global circulation models and two different emission scenarios to determine how climate trends and variability influence an adaptation option value. Using water-saving irrigation investments in California's Sacramento Valley as an example, results indicate that climate variability is an important predictor of private adaptation uptake but the influence of climate variability on adaptation shifts as the climate changes.

1 Introduction

Economic theory and empirical results show that a degree of adaptation will be autonomously carried out by private parties in response to climate change (Chambwera, et al. 2014). In response to rising temperature or changing precipitation patterns, individuals will migrate (Albouy, et al. 2016), adopt new technologies (Hallegatte and Dumas 2009) or encourage government investment in protective capital like levees (Kousky, et al. 2006) to moderate potential damages from climate change. Developing comprehensive climate change policy requires an understanding of the timing and magnitude of private adaptation since these measures may be complementary to mitigation efforts (Bosello, et al. 2010) or crowd out other climate and non-climate investments (De Bruin, et al. 2009;Wang and McCarl 2013) with potential for unintended consequences on macro-economic activity (Costinot, et al. 2016). Unfortunately, characterizing the incentives for private adaptation is challenging since these incentives depend on both climate change (shifts in long-term climate trends) and climate variability (time-varying variance in climate outcomes). This study uses downscaled climate projections[1] to isolate the role of climate trends *and* variability in private adaptation decisions.

Large-scale results from global circulation models (GCMs) are now frequently downscaled to make predictions at local scales. Individuals can use these predictions to update expectations of the future benefits and costs associated with adaptation investments. For instance, in areas where predictions suggest the future will be drier than the past, individuals may plant drought resistant crops, invest in water-saving infrastructure, or move to other areas to shield themselves from future scarcity and subsequent higher water prices. However, climate

[1] The IPCC differentiates between climate projections and climate forecasts. Climate projections are model-driven estimates of future climate. Climate forecasts or predictions are the "most likely" projection. We adopt these definitions throughout the paper.

change in many areas will also be characterized by greater temperature and precipitation variability. How climate variability influences adaptation depends on how easily adaptation actions can be adjusted in response to new information. When adaptation can be easily adjusted in response to recent temperature and precipitation (e.g., planting drought resistant varieties), climate variability influences adaptation through risk preferences (Burton 1997). A risk averse decision maker faced with greater climate variability will tend to engage in more of this type of adaptation (Heal and Kriström 2002).

Adaptation may also come in the form of discrete investments (e.g., switching to more efficient irrigation system) that are difficult or impossible to adapt in response to recent temperature and precipitation. Climate variability influences this type of adaptation through an option value (Chambwera, et al. 2014;Margulis, et al. 2010;Sturm, et al. 2016;Treasury 2009). When adaptation incurs costs that cannot be easily recouped and the benefits of the action are uncertain, there is an economic value (an option value) to delaying the action to collect more information about the benefits (Arrow and Fisher 1974;Henry 1974). In other words, when the future is uncertain, it pays to keep one's options open. While there is a fair amount of literature focused on option values for climate change mitigation (Golub, et al. 2014), there is far less focused on adaptation and especially private adaptation. Theoretical work shows that increased climate variability makes private adaptation more risky and causes individuals to delay these investments (Fisher and Rubio 1997;Narita and Quaas 2014;Wright and Erickson 2003). This suggests that projections of private adaptation based on perfect foresight assumptions will predict too much adaptation. However, these theoretical results may not carry-over to actual adaptation decisions since climate change is a non-stationary process and adaptation payoffs are often nonlinear (Saphores 2004).

This paper represents the first test of these theoretical results using actual down-scaled climate projections from four GCMs under two different CO_2 emissions scenarios.[2] Using an investment in water conservation in California's Central Valley as an example, we make three contributions to the economic literature on climate change adaptation. First, we show how actual GCM-based climate projections influence private adaption investments by contrasting optimal adaptation with backward- and forward-looking agents. Second, we allow for climate and market variability. This allows us to determine if climate variability is more influential than other sources of variability that influence adaptation decisions. Third, we characterize decision maker expectations of both climate and markets that would hasten private adaptation. Contrary to the theoretical findings, our results suggest that climate variability may not always lead to a delay in adaptation. However, climate variability may not be the most influential source of variability facing decision makers.

2 The Model

Our model is cast in terms of a risk-neutral farmer whose objective is to determine if and when to invest in a water-saving irrigation technology to maximize the expected present value of farm profits net of adaptation costs. The problem is one of optimally switching from a regime where the farmer employs a water inefficient irrigation technology to one where he employs a more water efficient technology. The optimal adaptation decision is influenced by 1) the

[2] Those studies that do utilize output from GCMs (Gersonius, et al. 2013;Venkatesh and Hobbs 1999;Woodward, et al. 2014) utilize two-period Monte Carlo simulation techniques that limit their applicability to actual adaptation investments whose benefits extend over multiple periods. The computational dynamic programming techniques we employ provide a more accurate estimate of the influence of climate variability than previous two-period models.

irrigated production process and 2) change and variability in climate and markets that shape expectations of future payoffs from conserving water. For example, increased climate variability leads to extreme events such as unprecedented droughts and heatwaves that will tend to encourage adaptation. However, climate variability also makes investments in adaptation more risky. Precipitation that is more variable may result in extreme drought but it will also result in more floods that lower the expected benefits of water-conservation. Climate change can encourage adaptation by increasing the expected returns from water conservation but climate variability can discourage adaptation by making water conservation more risky. Given expectations of future climate and market conditions, the farmer must choose when to move from the inefficient technology regime to the efficient technology regime by choosing a critical threshold in the aggregate water supply (e.g., river flow or reservoir level that serves farmer's fields). Adaptation becomes profitable from the farmer's perspective when the aggregate water supply falls below this threshold.

2.1 Irrigated Agricultural Production

The farmer produces a commodity whose price is given exogenously by P_y. Following Berck and Helfand (1990), Letey (1991), and Carey and Zilberman (2002), the farmer's production is represented by a Von-Liebig production function

$$y_i = \begin{Bmatrix} \gamma_i B X_i \ when \ X_i < X_i^* \\ y^* \ when \ X_i \geq X_i^* \end{Bmatrix} \ i = I, E \tag{1}$$

with $i = I$ corresponding to production using a water inefficient irrigation technology (e.g, furrow or flood irrigation) and $i = E$ corresponding to production using a water efficient irrigation technology (e.g., center pivot or drip irrigation).[3] y^* is the farmer's optimal level of production, X_i^* is the farmer's optimal water demand under technology *i* (what he would require for optimal production if unconstrained by water supply), and X_i is the amount of water employed in production. In a Von-Liebig (or plateau) model, production responds to the addition of a limiting input until a different input becomes limiting (Letey 1991). This reflects the fact that production inputs are not as readily substitutable as implied by smooth, concave functions. The farmer has applied other production inputs at such a level that water is the limiting input in production when $X_i < X_i^*$. When water is the limiting input, production will respond to increasing water availability according to $\gamma_i B X_i$ where B is a vector of all non-water inputs and γ_i is a scalar that reflects the efficiency of technology *i*. Another production input (e.g., land or canal size) becomes limiting at $X_i \geq X_i^*$.[4]

The total amount of water available for use by the farmer is represented by;

$$A(t) = \begin{Bmatrix} \theta \widetilde{W} \; if \; W(t) \geq \widetilde{W} \\ \theta W(t) \; if \; W(t) < \widetilde{W} \end{Bmatrix} \tag{2}$$

where $\widetilde{W}$ is an exogenously determined scarcity threshold, $\theta \widetilde{W}$ is the amount of water the farmer is entitled to divert under 'normal' conditions based on the farmer's water rights or shares[5], and $W(t)$ is the aggregate water supply at time *t*. This aggregate water supply may

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[3] It is assumed that yield-increasing effects of the new technology on production are negligible (Berck and Helfand 1990;Carey and Zilberman 2002;Letey 1991), leaving the focus of gains from adoption to rest solely on water savings from increased water efficiency. Thus we assume that $y_I^* = y_E^* = y^*$ so that we do not have a yield-increasing effect associated with adoption if both technologies operate at full potential. This assumption may be violated with if nutrient processing by agricultural crops is substantial. This is an area that may be explored in subsequent work.
[4] Von-Liebig production functions can be reconciled with smooth, differentiable production functions via aggregation (Berck and Helfand 1990). This specification is employed with the knowledge that it is not mutually exclusive to smooth production functions in the aggregate.
[5] We assume that $\theta \widetilde{W}$ cannot change due to the allocation of new rights.

reflect the flow of a river or canal or the depth of snowpack supplying water to the farmer. In times of relative water abundance $\left(W(t) \geq \widetilde{W}\right)$, a farmer may exercise their full water right. The model assumes shares have been acquired in the past and recurrent expenses associated with holding the share are negligible. In times of relative water scarcity $\left(W(t) < \widetilde{W}\right)$, the amount of water available to the farmer is restricted to a fixed proportion of the aggregate supply. This conditional water supply reflects the reality in many parts of the western U.S. where water rights were allocated on historic conditions and often exceed available supply.

The relationship between available water $A(t)$ and applied water X_i is as follows;

$$X_i = \begin{Bmatrix} X_i^* \ if \ A(t) \geq X_i^* \\ X_i < X_i^* \ if \ A(t) < X_i^* \end{Bmatrix} \tag{3}$$

Thus, $A(t) - X_i$ is the difference between water the farmer has available for production and how much he actually employs in production. If positive ($A(t) > X_i$), this difference represents the total amount of water left over after production and available for sale by the farmer. If negative ($A(t) < X_i$), this difference indicates how much water the farmer buys to supplement his available water for production. Investment in efficient irrigation technology helps tilt the difference of the two terms towards a surplus by reducing X_i.

The farmer can smooth his water supply by leasing/renting water rights in the spot market at price $P(t)$ per acre-foot. Periods of low *aggregate* water supply are assumed to correspond to periods of high water prices in the spot market. For simplicity, we assume the (inverse) demand for water on the spot market is isoelastic

$$P(t) = \left(\frac{W(t)}{\varphi(t)}\right)^{-\frac{1}{\varepsilon}} \tag{4}$$

where $\varphi(t)$ is a positive demand variable and $\varepsilon > 0$ is the price elasticity of demand.[6] An isoelastic demand function depicts constant elasticity and is chosen here to demonstrate the relative (short run versus long run) inelasticity of water demand to water price (Olmstead and Stavins 2009).

The farmer's optimal amount of applied water is determined by constrained profit maximization holding the technology constant. The farmer's optimized profit function at time t, derived by optimizing his instantaneous profit function, is

$$\Pi_i(P, W) = \max_{X_i} P_y \gamma_i B X_i - P(t)\big(X_i - A(t)\big) - C_i \tag{5}$$

where C_i represents the day-to-day fixed cost of operating the irrigation system under technology i. The farmer incurs this cost whether he invests or not. However, we allow for the possibility that C_i may increase (decrease) upon adoption of the modern technology due to say higher pressurization costs (greater energy efficiency) with the new system.

The relationship between agricultural production and the aggregate water supply is depicted in Figure 1. The bottom left quadrant depicts the discontinuous relationship between the aggregate water supply and the water available to the farmer in equation (2). The bottom right quadrant depicts the relationship between available water and applied water in equation (3). The upper right quadrant depicts the Von-Liebig production relationship in equation (1). Moving counter-clockwise from the bottom left quadrant illustrates how the aggregate water supply and water rights influence the use of water in the production process.

[6] To the extent that changes in a farm's water supply mirror changes in the aggregate supply, W and P will be negatively correlated as expressed in our isoelastic demand function.

Because farm profits are linear in applied water, the first-order condition arising from equation (5) suggests a bang-bang solution. When $P(t) \leq P_y \gamma_i B$ the farmer optimally chooses to apply X_i^*. Whether a farmer is a buyer or seller of water depends on the relative magnitude of the farmer's water right and optimal water demand. If $A(t) < X_i^*$, the farmer will purchase water to produce y^* given the von Liebig production function. As shown in Figure 1A, the need to purchase water will arise when the famer's water rights are lower than the optimal water demand ($\theta \widetilde{W} < X_i^*$) or aggregate water supplies are sufficiently low. If the farmer's water right exceeds his optimal water demand $\left(\theta \widetilde{W} > X_i^*\right)$, $W(t)$ must fall further than $\widetilde{W}$ to trigger water purchases (Figure 1B).[7] The von Liebig production function also implies that the farmer will sell excess water when water supplies are relatively abundant $A(t) > X_i^*$. Water sales arise when the farmer's water right exceeds his optimal water demand $\left(\theta \widetilde{W} > X_i^*\right)$. Otherwise, an investment in the more efficient technology is needed before the farmer will ever choose to sell water.

But when $P(t) > P_y \gamma_i B$ the value marginal product of water in irrigated agriculture is lower than the price of water on the spot market. As long as $P(t) > P_y \gamma_i B$, the farmer will terminate production and lease all of his available water. Since it would no longer be in use, the water-saving technology would provide no value to the agent. This suggests a nonlinear relationship between water price and the value of water-saving investments from the farmer's perspective.

2.2 Change and variability in the climate and markets

[7] In the razors edge case when the farmer's water right exactly equals his optimal water demand, the farmer only buys water when the water level falls to $\widetilde{W}$.

The spot price of irrigation water, $P(t)$, is a critical factor in the decision to adopt water conservation technologies since it determines how much a farmer must pay to offset below-optimal water availability and also determines how much compensation will be received if the farmer elects to lease water conserved from the new technology. There are two sources of change and variability that influence the spot price of irrigation water. First, a farmer is unable to perfectly predict how much water will be available for use in future years due to the unpredictability of river/canal flows and snowpack levels from year to year. This natural source of uncertainty is captured by modeling the evolution of aggregate water supply as a generalized Ito process:

$$dW = \alpha(W,t)dt + \sigma(W,t)dB_w \tag{6}$$

where $\alpha(W,t)$ is the instantaneous drift rate of the supply process, $\sigma(W,t)^2$ is the instantaneous variance and dB_w is the increment of a standard Brownian motion. A positive value for α implies aggregate water supplies are increasing while larger σ implies more volatility in water supply. Common stochastic processes such as geometric Brownian motion and Ornstein-Uhlenbeck processes are characterized by drift and volatility parameters that are not explicit functions of time. These specifications imply that the water supply process is stationary in that the relationship between $W(t)$ and $W(t+dt)$ varies only with how far apart in time they are but not with the specific points in time. When the drift and volatility terms are explicit functions of time, the farmer's water supply becomes nonstationary which is more consistent with long-term climatic impacts on hydrologic processes (Milly, et al. 2008).

Second, even if river flows could be predicted with certainty, future water prices will remain uncertain due to unpredictable changes in the demand for irrigation water (e.g., inability to predict future agricultural trends and population growth in the area). This demand uncertainty is captured by assuming φ follows a generalized Ito process

$$d\varphi = a(\varphi, t)dt + b(\varphi, t)dB_{\varphi} \tag{7}$$

where $a(\varphi, t)$ is the instantaneous drift rate, $b(\varphi, t)^2$ is the instantaneous variance and $E\left[dB_{\varphi}dB_{w}\right] = \delta dt$ is the covariance between shocks to water demand and the aggregate water supply with $\delta \in [-1,1]$. A larger value for a implies a faster rate of growth in water demand while larger b implies more volatility in water demand.

Figure 2 illustrates how these two sources of uncertainty lead to uncertainty in future water prices. Since river flows do not respond to changes in demand from year to year, aggregate water supply is perfectly inelastic. Farmers can form expectations of future water supplies (W) and water demand (φ) based on historic data or projections. However, unexpected changes in W and φ, governed by the stochastic differential equations in (6) and (7), can both lead to unexpected changes in the future spot price of irrigation water. Another appealing feature of the isoelastic demand specification is that unexpected shocks to the aggregate water supply will result in smaller shocks to water prices when aggregate water supplies are high.

2.3 The Adaptation Decision

Based on expectations of future profit, a farmer utilizing the old irrigation technology can choose to adopt the new irrigation technology when the aggregate water supply drops to W^*, which instantly changes production efficiency to $\gamma_E > \gamma_I$ and fixed production costs to $C_E \leq C_I$.[8] The time when optimally investing in the efficient irrigation technology is uncertain since future aggregate water supply W and water demand φ are uncertain. In addition to the fixed production costs, adopting the new irrigation technology requires a one-time investment cost. This investment cost M represents the cost of purchasing and installing the new irrigation technology.

In this discontinuous or threshold control setting, adopting a more efficient irrigation technology is akin to an uncertain investment decision and is made with the knowledge that all future investing decisions will be optimal. Based on traditional benefit-cost analysis, the efficient technology would be adopted when the expected present value of the profit increase $(\Pi_E - \Pi_I)$ equals or exceeds the investment cost

$$E[\int_0^\infty P({X_E}^* - {X_I}^*)e^{-\rho t}dt] - \int_0^\infty (C_I - C_E)\, e^{-rt}dt \geq M \tag{8}$$

Since P is stochastic, it is discounted by the risk-adjusted interest rate, ρ. $C_I - C_E$ is deterministic and thus discounted by the risk-free interest rate r.

However, when adoption of the efficient technology incurs a sunk cost, there is an incentive (an option value) to delay these decisions longer than suggested by benefit-cost analysis. The delay allows the farmer to respond to new information on how scarce and how valuable water will be in the future. To account for the option value, the farmer must evaluate, at

[8] If the drift and variance parameters in equations (6) and (7) do not explicitly depend on t (non-homogenous differential equation), the critical streamflow that triggers adaptation will be independent of time. Otherwise, the critical adaptation threshold changes as time passes.

each instant in time, whether or not the water-saving irrigation technology should be adopted. The optimal technology adoption decision (W^*) satisfies[9]

$$V(W_0, \varphi_0, t) = \max_{W^*(t)} E_0 \left[\int_0^{t^*} \Pi_I(W, \varphi) e^{-\rho t}\, dt + \left\{ [V(W, \varphi) - M] e^{-\rho t^*} \right\} \right] \tag{9}$$

subject to dW, $d\varphi$, $W(0) = W_0, \varphi(0) = \varphi_0$ where t^* is the expected time the aggregate water supply reaches W^*. The evaluation at each instant in time maximizes expected discounted farm profits from that point forward by making a simple choice to continue with the water inefficient technology or to adopt the more water efficient technology at cost *M*.

Because of the multi-dimensional nature of the state space, the critical water supply level that triggers technology adoption (or adaptation) is characterized by a curve, $W^*(\varphi, t)$. This curve solves the following value matching condition $V_I(W^*(\varphi, t)) = V_E(W^*(\varphi, t))$ where

$$V_E(W^*(\varphi, t)) = E_t \int_t^{\infty} \Pi_E(W^*(\varphi, t)) e^{-\rho t} dt - M \tag{10}$$

The value matching condition ensures the total payoff under the inefficient and efficient technologies are equal and acts as a boundary condition for the inefficient technology regime. The payoff from continuing with the inefficient technology, V_I, is the solution to the partial differential equation

$$\rho V_I = \Pi_I + \frac{\partial V_I}{\partial t} + a(\varphi, t) \frac{\partial V_I}{\partial \varphi} + \alpha(W, t) \frac{\partial V_I}{\partial W} + \frac{b(\varphi, t)^2}{2} \frac{\partial^2 V_I}{\partial \varphi^2} + \frac{\sigma(W, t)^2}{2} \frac{\partial^2 V_I}{\partial W^2} + b\sigma\delta \frac{\partial^2 V_I}{\partial \varphi \partial W} \tag{11}$$

[9] The adaptation problem can be stationary or nonstationary. Stationarity is typically assumed by allowing for an infinite planning horizon and assuming the stochastic processes are described by non-autonomous stochastic differential equations such as geometric Brownian motion. Here we relax the stationary assumption by assuming the parameters of the stochastic processes are explicit functions of time.

The left-hand side of (11) is the return a farmer would require to delay technology adoption over the time interval *dt*. The right-hand side is the expected return from delaying adoption over the interval *dt*. When (11) holds as an equality, it is optimal to delay adopting the more efficient irrigation technology (remain in the inefficient technology regime). When (10) and (11) are satisfied, a farmer has optimally delayed adaptation until the efficient technology provides a payoff as large as the inefficient technology.

The multi-dimensional nature of the state space and the dual technology regimes require numerical methods to approximate $V_I(\varphi, W)$ and $V_E(\varphi, W)$. We approximate these unknown value functions over a subset of the state space using piecewise linear basis functions (Balikcioglu, et al. 2011;Marten and Moore 2011). The approximation procedure solves for the $2 \times n^2$ basis function coefficients which satisfy (10) – (11) at a set of n nodal points spread evenly over the two-dimensional state-space. Specifically, the unknown value functions are approximated with a linear spline constructed using upwind finite difference approximations. Instead of an explicit solution, the technology adoption curve, $W^*(\varphi, t)$, is the set of n points where these conditions are met.

3. Adapting to Water Scarcity in the Sacramento Valley

To illustrate, we apply the framework and solution technique to the decision to invest in water-saving irrigation technology in the Sacramento Valley of California (see Figure 3). The Sacramento Valley is the northern portion of California's Central Valley - the most productive agricultural region in the country. Agricultural production in the Sacramento Valley relies on irrigation and over 70 percent of the annual irrigation supply comes from surface water. Surface water is annually replenished by melting snowpack in the Sierra Nevada Mountains. This water is brought to agricultural producers in the valley via four main rivers: the Sacramento, Feather, Yuba, and American.

3.1 Characterizing the investment decision in the Sacramento Valley

Model parameters are presented in Table 1. Our investment decision is based on a farm producing 5.5 tons of alfalfa per acre annually ($y = 5.5$) which is the average of 2012 and 2013 alfalfa production in Yuba County in the Sacramento Valley.[10] Alfalfa constitutes more irrigated hectares than any other crop in California (Tindula, et al. 2013). Unlike high value crops like almonds and pistachios, the vast majority of alfalfa area is irrigated using relatively inefficient surface irrigation methods. The price of alfalfa is $p_y = \$197$ per ton, which is consistent with 2013 County Crop Reports from the Sacramento Valley.

According to the U.S. Department of Agriculture Farm and Ranch Irrigation Survey (https://www.agcensus.usda.gov/index.php), 3.8 to 5 acre-feet of irrigation water was applied in the production of alfalfa in California in 2013. To yield optimal water demand at the upper end of this range, the water usage parameter under the inefficient technology is $\gamma_I = 1.1$. The exogenously determined scarcity threshold is set to 35 percent of the average historic flow in the Yuba River ($\widetilde{W} = 25{,}000{,}000$ annual acre feet). The farmer is neither a buyer nor seller of water during normal operating conditions: $\theta = \frac{X_I^*}{\widetilde{W}} = 0.0000002$. The water usage parameter under the efficient technology is $\gamma_E = 2$ which yields annual water savings of 2.25 acre-feet per acre following investment. These savings are consistent with switching from flood to center pivot irrigation in the semi-arid areas in the western United States (Brown 2008). The $1,000 per acre

[10] For details see http://www.co.yuba.ca.us/Departments/Ag/.

investment cost is obtained from California estimates for the cost of center pivot irrigation by the Natural Resources Conservation Service of the United States Department of Agriculture (NRCS, 2009).

There is little data on actual transaction prices for irrigation water in the Sacramento Valley. To obtain a value for the drift and volatility of the demand parameter and the elasticity of water demand, we utilize water price data from the Water Transfer Level Dataset compiled by researchers at UC-Santa Barbara. This dataset draws from water transactions reported in the monthly trade journal the *Water Strategist* and its predecessor the *Water Intelligence Monthly* from 1989 through February 2010. The dataset includes the year of a water transfer, the acquirer of the water, the supplier, the amount of water transferred, the proposed use of the water, the real price of the trade (in 1987 dollars), the terms of the contract, and the issue of the *Water Strategist* where the data was reported. To obtain a dataset of prices relevant to agricultural producers in the Sacramento Valley, we only include prices from transactions that took place in northern California where the lessor, lessee, seller, or buyer is an agricultural user (i.e., irrigator, an irrigation district, a water district, a farmer, a rancher, a canal company, a ditch company or an individual). This leaves 277 water transactions between 1989-2009. As shown in Figure 4, there is a clear negative relationship between aggregate water supplies and the reported water price consistent with an iso-elastic demand function. Applying ordinary least squares indicates irrigation water demand is elastic: $\varepsilon = 1.94$.

However, the relationship in Figure 4 indicates that demand shocks are common and would limit a farmer's ability to predict water price even if aggregate water supplies were known with certainty. Given our estimate for demand elasticity, we use equation (4) to solve for the $\varphi(t)$ implied from our time series datasets for $P(t)$ and $W(t)$. This approach generates a 23-year time series for $\varphi(t)$ that captures trends and variability in irrigation water demand in the Sacramento Valley.

The stochastic process governing $\varphi(t)$ may be either difference stationary or trend stationary. The former describes widely used stochastic processes such a arithmetic Brownian motion and geometric Brownian motion which are characterized by a stochastic trend. The latter describes various mean reverting processes, which are characterized by a deterministic trend. An augmented Dickey Fuller test is performed to test whether $\varphi(t)$ are trend or difference stationary. The null hypothesis corresponding to $\varphi(t)$ being geometric Brownian motion cannot be rejected. We conclude $\varphi(t)$ evolves according to a geometric Brownian motion: $a(\varphi, t) = a\varphi$ and $b(\varphi, t) = b\varphi$. The drift and volatility parameters of the geometric Brownian motion process for $\varphi(t)$ are estimated by applying ordinary least squares to the first order (Euler) approximation of the GBM process $(\varphi_{t+1} - \varphi_t)/\varphi_t = a + \epsilon_t$ where ϵ_t is normally distributed with mean zero and standard deviation b. The regression results suggest that the demand for irrigation water is increasing at over 43 percent per year $(a = 0.437)$ with an 80 percent volatility around this trend $(b = 0.798)$.

3.2 Incorporating climate change and variability

To capture the effect of climate change and variability in the Sacramento Valley, we focus on climate projections for annual streamflow (in acre feet) in the Yuba River watershed.[11] While streamflow magnitude and timing within a watershed depend on area and elevation (Null, et al. 2010), watersheds in California's Sierra Nevada are known to be spatially and temporally

[11] Our analysis focuses on streamflow instead of natural flow. Streamflow considers diversions and more closely matches actual water in the river in an area. Streamflow conditions are consistent with measurements at IRF Smithville (below Englebright Lake) which is a focal point of management in the watershed.

correlated with neighboring basins (Lundquist, et al. 2004;Peterson, et al. 2008). In other words, neighboring streams behave in similar ways. Weather patterns are spatially correlated throughout California (Peterson, et al. 2008), while snowmelt is temporally correlated for similar elevations (Lundquist, et al. 2004).

Meteorological data (air temperature, precipitation, and relative humidity) downscaled from general circulation models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (Knutti and Sedláček 2013;Taylor, et al. 2012) were used as input for a hydrologic model developed for the western Sierra Nevada with the Water Evaluation and Planning System (Yates, et al. 2005;Young, et al. 2009).[12] Four GCMs were forced with two different representative concentration pathways (RCP) to capture regional meteorology and a range of emissions and economic conditions.[13] Representative concentration pathway +4.5 W/m^2 (RCP4.5) assumes maximum CO_2 emissions of 450 parts per million (ppm), global population that peaks mid-century, and introduction of a resource-efficient technology. Representative concentration pathway +8.5 W/m^2 (RCP8.5) assumes maximum CO_2 emissions of 850 ppm, continuously increasing global population, and slow economic growth. This gives us eight short-term (2001-2050) streamflow projections (in acre feet). To illustrate how the climate-driven models alter streamflow projections and farmer expectations, we also use a modeled historical dataset consistent with observed streamflow in the Yuba River (see Figure 5) to generate a hindcast of streamflow in the Yuba River from 1951 to 2000.

An augmented Dickey Fuller test is performed to test whether the streamflow projections and hindcasts are consistent with Geometric Brownian Motion (GBM). If $w = \ln(W)$ is normally

[12] Downscaled meteorological data based on these GCMs was obtained from the CMIP5 hydroclimate archive (Brekke, et al. 2013) and prepared using bias-corrected constructed analogues (Maurer 2010).
[13] See Appendix for more information on the GCMs used in this study.

distributed, Ito calculus ensures W must be log-normally distributed and consistent with GBM. We reject the null hypothesis that w is normally distributed for all climate models.[14] Thus, we conclude that W is trend stationary and adopt a mean-reverting process to describe the evolution of W. However, traditional mean-reverting processes revert to a constant mean. This approach would ignore trends in aggregate water supply produced by the climate models. Instead, we follow Lo and Wang (1995) and assume that aggregate water supply reverts to an affine trend $\bar{W} + \mu t$:

$$d(W - \mu t) = \alpha(\bar{W} + \mu t - W)dt + \sigma dB_w \tag{12}$$

This process is the sum of a zero-mean stationary autoregressive Gaussian process and a deterministic linear trend. This can be rearranged to yield:

$$dW = \alpha(g(t) - W)dt + \sigma dB_w \tag{13}$$

where $g(t) = \frac{\mu}{\alpha} + \bar{W} + \mu t$.

Estimates of $\alpha, \mu,$ and $\bar{W}$ can be found for each climate model and each emissions scenario by noting that the trending process is consistent with the detrended streamflow data reverting to a constant mean

$$d\omega = \alpha(\bar{W} - \omega)dt + \sigma dB_w \tag{14}$$

where $\omega = W - \mu t$. Parameters are estimated by applying ordinary least squares to the first order (Euler) approximation of the mean-reverting process in equation (14): $\omega_{t+1} - \omega_t =$

[14] This runs counter to Fisher and Rubio (1997) and Bhaduri and Manna (2014) who assume a GBM for the stochastic evolution of water supply based on the log-normal distribution of water flow. Focusing only on variability in annual streamflow only captures part of the effect of climate change. In many areas, climate change manifests as more precipitation falling as rain instead of snow. Even if the annual total is unchanged, these shifts from snow to rain will manifest as inter-annual variability in streamflow.

$\alpha(\bar{W} - \omega_t) + \epsilon_t$ where ϵ_t is normally distributed with mean zero and standard deviation σ. We follow this process for all eight streamflow projections (2001-2050) and the streamflow hindcast (1951-2000). Results are presented in Table 2.

Differences in future trends across the models can be ascertained by examining $\bar{W}$ and μ. Higher values for $\bar{W}$ suggest a deterministic trend with a higher intercept. Positive (negative) values for μ suggest that streamflow is trending up (down). Streamflow persistence from year to year is captured by α. Lower (higher) values of α suggest a slower (faster) return to the deterministic trend following a shock. Higher values for σ suggest more variability around the deterministic trend.

Comparing parameter estimates under the historic hindcast (1951-2000) to estimates under the short-term climate projections (2001-2050) indicates the general implications of climate change and variability in each GCM-RCP combination (see Figure 6). The parameters estimated under two of the climate models (CCSM4.1, CNRM-CM5.1) suggests that the future will be wetter but the other two models (MIROC5.1, MIROC-ESM) suggest the future will be drier. All eight short-term climate projections suggest future streamflow will be more volatile.

The stochastic differential equation in (12) allows us to rewrite the partial differential equation in (11) as an ordinary differential equation by noting that time only influences the value function through the affine trend in streamflow: $\frac{\partial V_I}{\partial t} = \frac{\partial V_I}{\partial W}\frac{\partial W}{\partial t} = \frac{\partial V_I}{\partial W}(\mu + \sigma)$.[15] By substituting for $\frac{\partial V_I}{\partial t}$ and rearranging, equation (11) can be rewritten as:

[15] The analytic solution to equation (12) is $W(t) = \bar{W} + \mu t + \sigma \int_0^t e^{\alpha(s-t)} dB_w$ such that $\partial W/\partial t = \mu + \sigma$.

$$\rho V_I = \Pi_I + a(\varphi,t)\frac{\partial V_I}{\partial \varphi} + [\alpha(W,t)+\mu+\sigma]\frac{\partial V_I}{\partial W} + \frac{b(\varphi,t)^2}{2}\frac{\partial^2 V_I}{\partial \varphi^2} + \frac{\sigma(W,t)^2}{2}\frac{\partial^2 V_I}{\partial W^2} + b\sigma\delta\frac{\partial^2 V_I}{\partial \varphi \partial W} \quad (15)$$

which allows us to interpret the adaptation decision as a constant threshold in the Yuba River streamflow $W^*(\varphi)$. A linear climate change trend will shift the optimal adaptation decision but will not cause it to change over time.[16]

3.3 *Climate adaptation under different expectations of the future*

Given the parameter values in Table 1, we approximate V_I and V_E over a state space that extends from 0 to 211,470 in the φ dimension and 1 to 700 in the W dimension. This state space implies a range of possible water prices from $0 to $560 per acre feet which easily encompasses the range of water prices reported in the *The Water Strategist* in northern California. The value of the water efficiency investment option, $V_I(W,\varphi)$, is decreasing in φ. However, the value of the water efficiency investment option may be increasing or decreasing in W. When streamflow is low, the water price is high and the farmer is leasing all water so an increase in W means a farmer has more water to lease. When the streamflow is high, increases in W lower the price at which conserved water could be sold.

Approximating $V_I(W,\varphi)$ and $V_E(W,\varphi)$ allows us to calculate the critical adaptation curve that would trigger investment in new water-saving irrigation infrastructure (see Figure 7). The contour lines show the price of water at different combinations of W and φ. The black line shows the adaptation threshold based on the modeled historic streamflow (1951-2000). The

[16] This result relies on climate change causing a linear affine trend in the mean streamflow level $\overline{W}+\mu t$. If the passage of time leads to nonlinear changes in mean streamflow, the critical adaptation threshold will change over time $W^*(\varphi,t)$.

optimal investment decision depends on both the aggregate supply of water, W, and the demand for irrigation water in the area, φ. When the current state of the world, defined by pair $(W, \varphi,)$, is in region I, no change should be made to the irrigation technology. In this region, the value of the option to invest exceeds the expected net present value of farm profits if the water conservation technology were adopted. As the demand for water increases, the cost of acquiring water increases during water shortages and the value of conserved water increases during normal periods. A sufficiently large increase in the demand for irrigation water (rightward movement along the x-axis into region II) will trigger a water-saving investment regardless of the water supply (y-axis). Because both W and φ are stochastic, water price becomes a poor predictor of adaptation behavior. For example, an $80/acre foot water price is observed in both region I and II.

Region III highlights the nonlinear relationship between water demand and the value of investing in water conservation during water shortages. An increase in the demand parameter above approximately 80,000 will increase the water price enough to cause the farmer to adopt the water-saving irrigation technology regardless of the streamflow. But when streamflow is below 20 million acre feet, an additional increase in the demand parameter above approximately 100,000 makes it optimal to delay the water conservation investment once again. Delaying the investment is optimal in region III because it is sufficiently likely that the water price will stay high enough (above $217/acre feet) to encourage the farmer to stop production and temporarily lease all water rights. In other words, it is unlikely that the farmer will use the water-saving irrigation technology in region III. Because of the stochastic aspect of the model, a farmer that is currently leasing all his water rights would still find it optimal to invest in water conservation when the demand parameter is between 80,000 and 100,000. In this small window, demand is sufficiently strong to encourage water conservation but not so strong that the farmer expects to lease his entire water right for the foreseeable future.

The adaptation threshold in Figure 7 is consistent with a backward-looking farmer that bases expectations of future streamflow on his observations of past streamflow. A farmer may also be forward-looking and base expectations of future streamflow on climate-based projections. Climate projections that suggest the future will be wetter (CCSM4.1 with RCP 8.5, CNRM-CM5.1 with RCP 8.5) shift the adaptation threshold to the right suggesting adaptation will be delayed when future climate projections are incorporated into the adaptation decision (i.e., requires a higher water price to trigger investment in water conservation). Climate projections that suggest the future will be drier and/or more volatile (CCSM4.1 with RCP 4.5, CNRM-CM5.1 with RCP 4.5, MIROC5.1, MIROC-ESM) shift the adaptation threshold to the left suggesting climate projections will hasten adaptation.

However, each climate projection generates a separate adaptation threshold that only defines the optimal adaptation decision when future climate is characterized by that climate projection. Unfortunately, a farmer cannot assess the relative likelihood of the different climate projections and must assign subjective weights to each adaptation threshold. Figure 8 compares the adaption threshold of a backward-looking farmer to adaptation for two different types of forward-looking farmers. A forward-looking farmer may adapt based on an average of all eight adaption thresholds (red line in Figure 8). This threshold would be consistent with a farmer that is ambiguity neutral and gave each adaptation threshold an equal weight. The climate change projections cause the farmer's adaptation threshold to shift to the left. This suggests that a farmer is more likely to invest in adaptation (i.e., invests at a lower water price) when he bases his expectations of future streamflow on climate projections. However, climate trends are not responsible for the increased likelihood of adaptation. An ambiguity neutral farmer that focuses only on climate trends generated from GCMs and ignores the variability in the climate forecasts would invest in adaptation at nearly the same time as a farmer that formed expectations based on historic streamflow data. Climate projections will only encourage more expedient adaptation when the farmer accounts for the inter-temporal variability in the climate projections.

A forward-looking farmer may also base adaptation decisions only on the worst-case projection. A focus on worst-case scenarios is consistent with ambiguity aversion in a maxmin expected utility specification (Gilboa and Schmeidler 1989). The green line in Figure 8 shows that an ambiguity averse farmer will invest in climate change adaptation before an ambiguity neutral famer. From the farmer's perspective, the worst-case scenario will be the one that yields the lowest discounted expected farm profits. Since a drier future implies a farmer's water rights will be more valuable, the worst-case scenario in terms of discounted expected farm profits is where the future is wetter than the past: CNRM-CM5.1 and RCP 4.5. A wetter future lowers the expected price of irrigation water in the future and reduces the incentive to invest in water conservation. However, this worse-case projection also suggests future streamflow will be much more volatile than the past. This volatility in future streamflow works to shift the critical threshold to the left and hasten adaptation.

To indicate regions of the state space that have been observed historically, we plot price and streamflow combinations from 1990 through 2008. In 1990, water demand is so low that the option to invest exceeds the expected net present value of farm profits with the more efficient technology regardless of whether farmers are backward- or forward-looking. By 1992, only a forward-looking ambiguity averse farmer will choose to adopt the water conservation technology. By 1998, water demand increases enough to make investment in the water-efficient technology economically viable regardless of the way farmers form expectation of the future. A forward-looking, ambiguity averse farmer would adapt four years earlier than an ambiguity neutral farmer or a backward-looking farmer. But by 2002, water demand drops enough to move the farmer back over the adaptation curve. This temporary decline in water demand does not mean that the farmer regrets investing in the water conservation technology. The critical adaptation threshold is robust to stochastic shocks meaning that water demand need only cross the adaptation threshold; not remain above it.

3.4 The influence of change and variability in the climate and markets

The primary benefit of our approach is the ability to isolate the effect of changes in trends and variability from both climate and market sources on the adaptation decision. This approach allows us to determine whether short-term accuracy is more important than long-term trends. To investigate the effect of change and variability, we look at how a 25 percent increase and decrease in the market trend (a), market variability (b), climate trend ($\bar{W}$), and climate variability (σ) each impact the critical water price (i.e., critical demand parameter) that triggers adaptation under normal streamflow conditions and during water shortages. An immediate investment in water conservation will maximize the value of the farm when the water price crosses the thresholds from below.

Panels A and B in Figure 9 show the effect of climate trends and variability when the average annual streamflow is 70 million acre feet. Under these normal streamflow conditions, a drier and more volatile future will encourage more expedient adaptation. If a farmer expects the future to be wetter, the value of conserved water is lower which lowers the expected net present value of the conservation investment. As a result, the critical water price needed to trigger adaptation will be higher with expectations of a wetter future. More climate variability does not lead to a similar delay in adaptation. The critical price that triggers adaptation declines as climate variability increases, regardless of the way farmers form expectations of the future. While more stochasticity tends to increase the option value and encourage a delay in sunk cost investments, this will not always be the case in highly nonlinear models (Saphores 2004). The plateau production function and the ability to lease all water rights when the price of water is greater than its value in agricultural production, makes the payoff from adaption highly nonlinear over the relevant state space.

However, climate variability encourages a delay in adaptation during water shortages. Figure 10 shows how a more volatile future will increase the critical water price threshold when the farmer is forward-looking and ambiguity neutral and when average annual streamflow is 15 million acre feet,. During water shortages, increased streamflow variability has a larger impact on the adaptation option value than on the expected net present value of farm profits under the inefficient technology. In areas where water availability is expected to decline over time, the role of climate variability will also change. While climate variability in the short term encourages adaptation, climate variability in the long term will delay adaptation. This suggests that with a drier and more volatile future, some individuals may never find it optimal to invest in water conservation even if they continue to use irrigation water for agricultural production.

Climate is not the only relevant source of change and variability that influences the water conservation investment. Panels C and D in Figure 9 show that a faster growing and less volatile water market will encourage more expedient adaptation during normal streamflow conditions. Faster demand growth increases the expected net present value of the water conservation investment. This relationship persists regardless of how the farmer forms expectations of future streamflow and during water shortages. Decreased variability in local water markets makes an investment in water conservation less risky. With a less risky adaptation decision, a farmer will require a smaller burden of proof before investing in water conservation.

5. Conclusions

Large-scale results from global circulation models (GCMs) are frequently downscaled to make predictions at local scales. However, there is little understanding of how these local predictions influence adaptation decisions. The study uses an application to water conservation investments in the Sacramento Valley of California to illustrate how projected climate trends and the uncertainty in these projections influence private adaptation. In general, results suggest that forward-looking farmers that base expectations on downscaled projections will adapt to climate change sooner than backward-looking farmers that base expectations on historic conditions. These results hold regardless of individual preferences for ambiguity that arise due to the inability to assess the likelihood of any single climate projection. The results also call into question three commonly held beliefs concerning climate change and adaptation.

The first is that climate variability should discourage adaption investments. A common finding in the real options literature is that a greater inability to predict future environmental and market conditions make investments in environmental protection more risky and will tend to discourage those investments. Our results only partially confirm this finding. When a market creates an incentive to adapt, variability in that market creates an incentive to delay adaptation due to an adaptation option value. However, the same is not always true for climate variability.

Increases in climate-induced streamflow variability during water shortages delay adaptation similar to market variability. However, climate variability works to encourage adaptation with the historic streamflow conditions that will persist in the near future. In the near term, market and climate variability create countervailing effects on adaptation investments. Public investments in adaptation such as investments in instream storage that decreases streamflow variability will crowd out private adaptation decision in the near future but may spur adaptation investment in the future if water shortages become more severe and more frequent

The second commonly held belief is that adaptation is more influenced by climate variability than economic sources of variability. In our water conservation investment in the Sacramento Valley of California, the critical water price threshold that triggers adaptation is more sensitive to changes in market variability than climate variability. This result suggests that policies that destabilize water markets may be more detrimental to incentives to invest in adaptation than greater variability in temperature and precipitation.

The third commonly held belief is that climate change trends are a good predictor of adaptation behavior. While adaptation is more sensitive to climate trends, focusing only on climate-driven streamflow trends causes the farmer to wait until the water price rises 5 percent higher than the optimal water price trigger. Climate-driven projections of future water availability only trigger a more expedient investment in adaptation if the farmer is forward-looking and incorporates the variability in climate projections. Thus, a drier future may not create the right incentives for private adaptation if future streamflow is more predictable and markets are more unpredictable.

This study also provides a framework for using real options analysis to investigate climate change adaptation by solving a non-autonomous optimal stopping problem. While real options analysis has been frequently cited as a useful framework for investigating climate change adaptation, there has been little guidance on how analysis should be done. This modeling framework allows for the isolation of change and variability in climate and input markets and the identification of these factors on the intensive margin of agricultural production. However, there are also extensive margin adjustments such as adopting different crops and shifting production geographically that we leave for future work (Olmstead and Rhode 2011). The inability to achieve analytic results means our results may not be generalizable to other watersheds or other water markets much less other forms of adaptation investment. Future work is needed to apply our modeling framework in other watersheds and in other water markets.

Appendix

Table 1A: Features of the Atmosphere-Ocean General Circulation Models (AOGCMs) and Earth System Models (ESMs) used in our study. Column 1 indicates model name and calendar year of first publication of each model. Column 2: Sponsoring institutions. Subsequent columns indicate presence or absence of key model components.

Model Name	**CCSM4.1** (2010)	**CNRM-CM5.1** (2010)	**MIROC5.1** (2010)	**MIROC-ESM** (2010)
Institution	US National Center for Atmospheric Research	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
Atmosphere	CAM4	ARPEGE-Climat	CCSR/NIES/FRCGC AGCM6	MIROC-AGCM
Aerosol	Interactive	Prescribed	SPRINTARS	SPRINTARS
Atmos Chemistry	Not implemented	3-D linear ozone chemistry model	Not implemented	Not implemented

Land Surface	Community Land Model 4	SURFEX (Land and Ocean Surface)	MASTSIRO	MATSIRO
Ocean	POP2 with modifications	NEMO	COCO4.5	COCO3.4
Ocean Biogeochemistry	Not implemented	PISCES	Not Implemented	NPZD-type
Sea Ice	CICE4 with modifications	Gelato5 (Sea ice)	Included	Included

Source: Flato, et al. (2013)

Table 1. Model parameter values

Parameter	Value	Source
P_y	$197/ton	2013 Yuba County Crop Report
y	5.5 tons per acre annually	California Agricultural Statistics 2013 Crop Year
γ_I	1.1	USDA 2013 Farm and Ranch Irrigation Survey
γ_E	2	Brown, 2008
M	$1,000/acre	Natural Resources Conservation Service
θ	0.0000002	
$\widetilde{W}$	25 million annual acre feet	
ρ	0.04	
ε	1.94	estimated from *Water Strategist* data
a	0.437	estimated from *Water Strategist* data
b	0.798	estimated from *Water Strategist* data

Table 2. Stochastic differential equation parameters for Yuba River streamflow

Period	**Emissions scenario**	**Climate model**	μ	$\bar{W}$	α	σ
1951-2000			0.001	71.297	400.990	214.062
2001-2050	Moderate (RCP4.5)	CCSM4.1	0.043	70.846	279.699	515.765
		CNRM-CM5.1	1.058	60.202	329.652	496.667
		MIROC5.1	0.133	67.689	311.470	430.293
		MIROC-ESM	0.304	53.579	325.578	337.073
2001-2050	Severe (RCP8.5)	CCSM4.1	-0.093	81.933	384.627	449.965
		CNRM-CM5.1	0.491	70.157	294.686	351.943
		MIROC5.1	0.026	67.665	382.480	310.940
		MIROC-ESM	-0.307	74.434	389.442	354.830

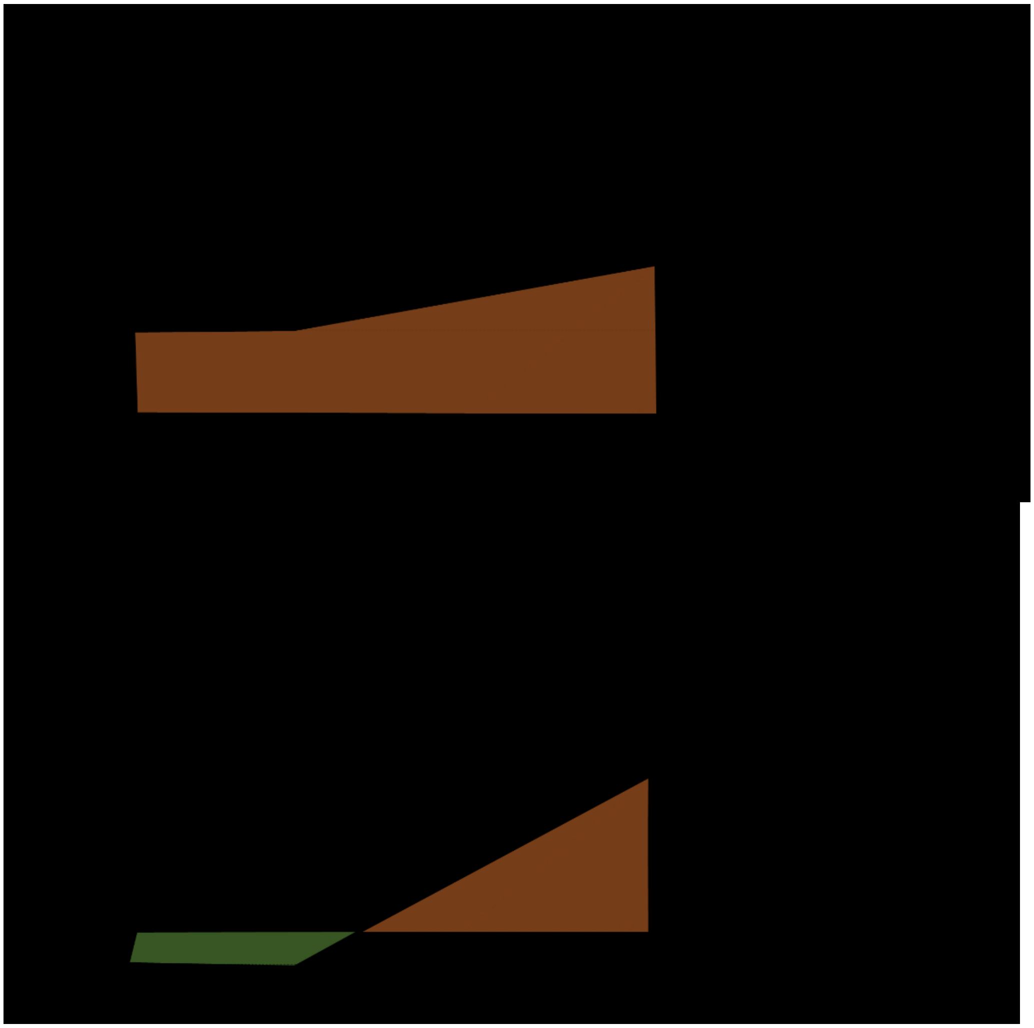

Figure 1. Relationship between streamflow, applied water, and production when water rights are (A) less than and (B) greater than optimal water demand

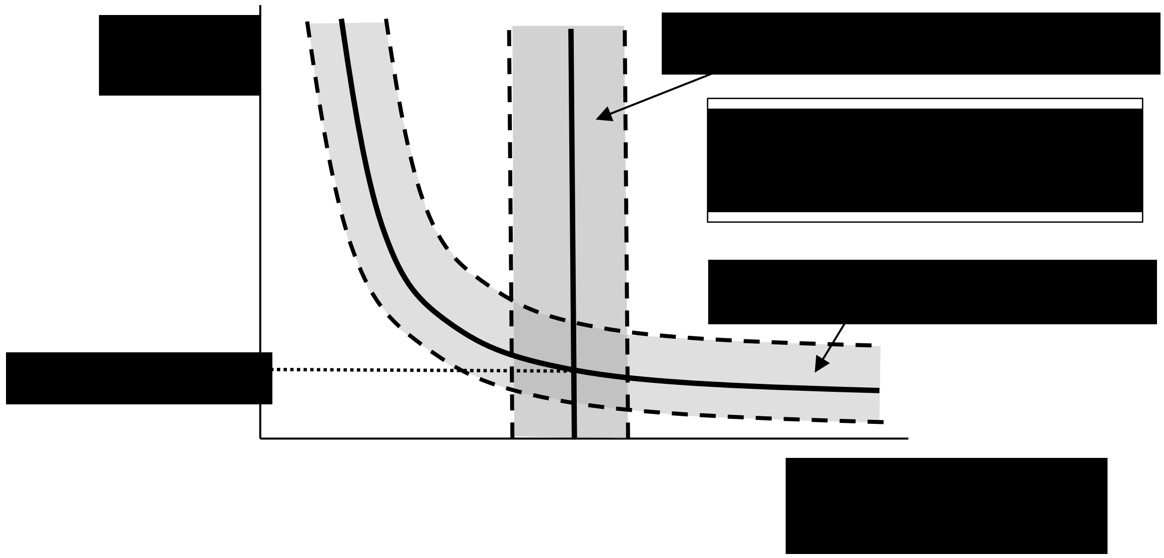

Figure 2. Uncertainty in irrigated water prices originating from uncertainty in future river flows (supply) and demand for irrigation water.

Figure 3. Yuba River study area

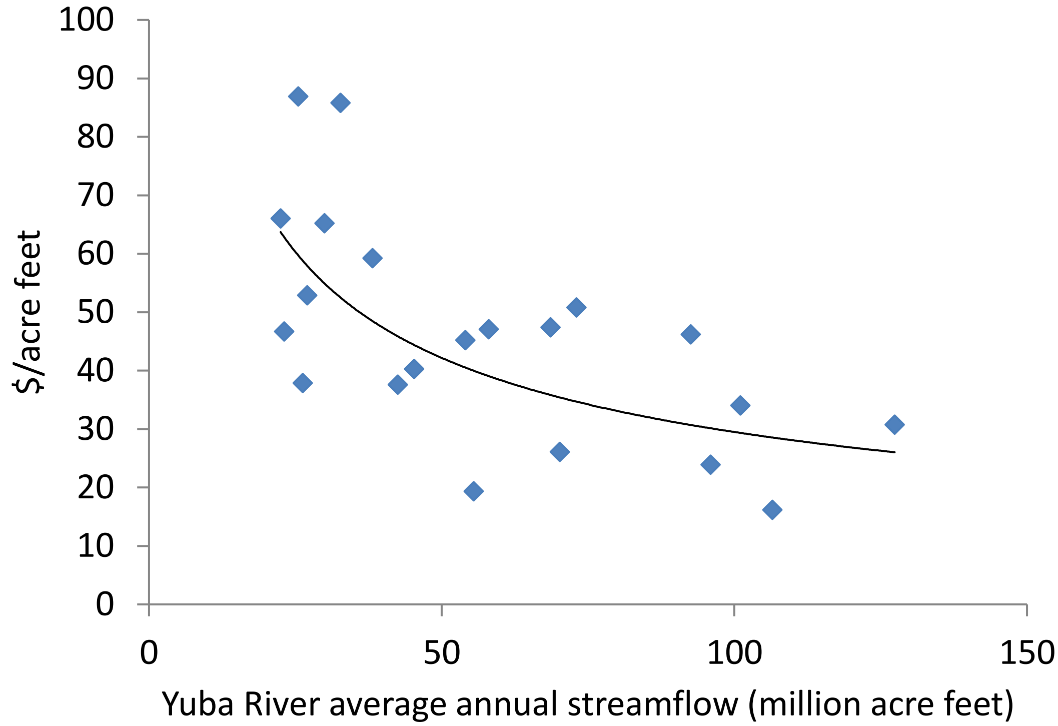

Figure 4. Relationship between *Water Strategist* reported price for irrigation water in northern California and Yuba River streamflow indicates iso-elastic demand function

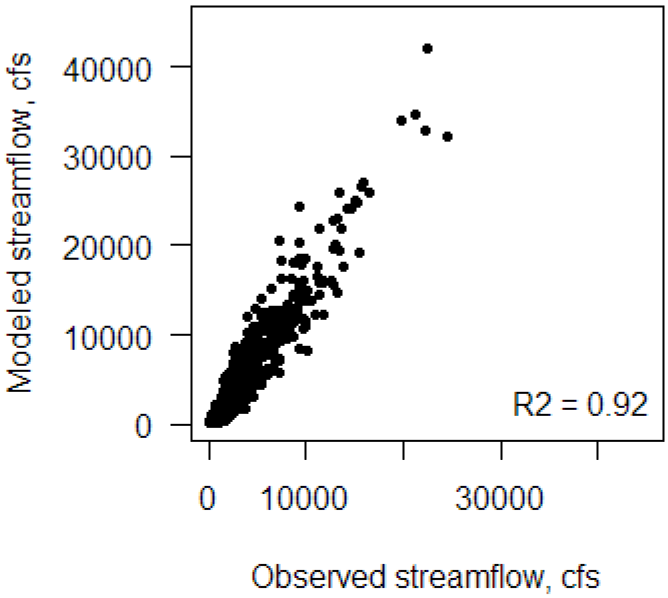

Figure 5. Comparison of observed streamflow in the Yuba River at Smartville with coupled climate-hydrologic model projections

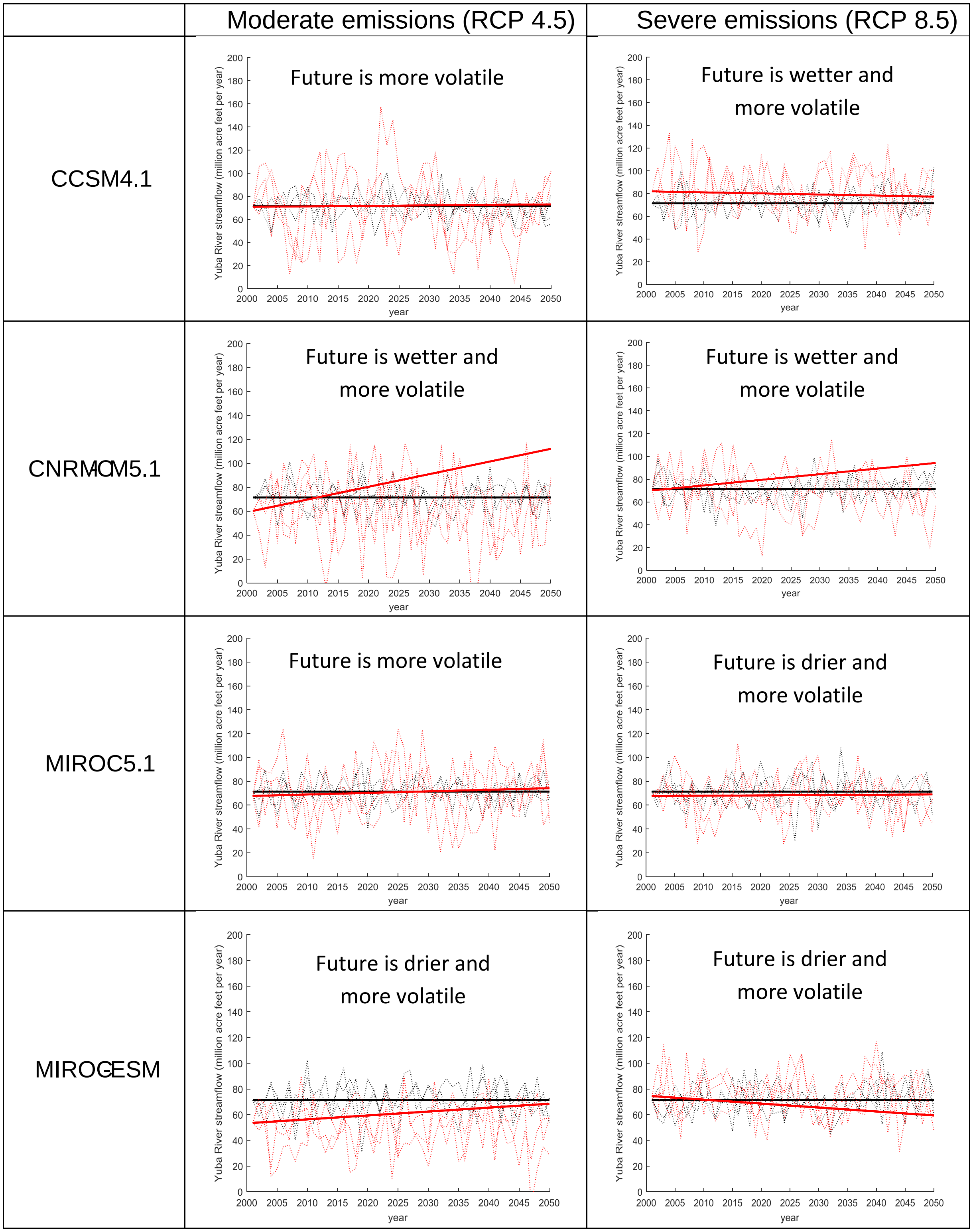

Figure 6. Differences between historic (black lines) and future (red lines) Yuba River streamflow produced from four different general circulation models (GCM) under two different representative concentration pathways (RCP).

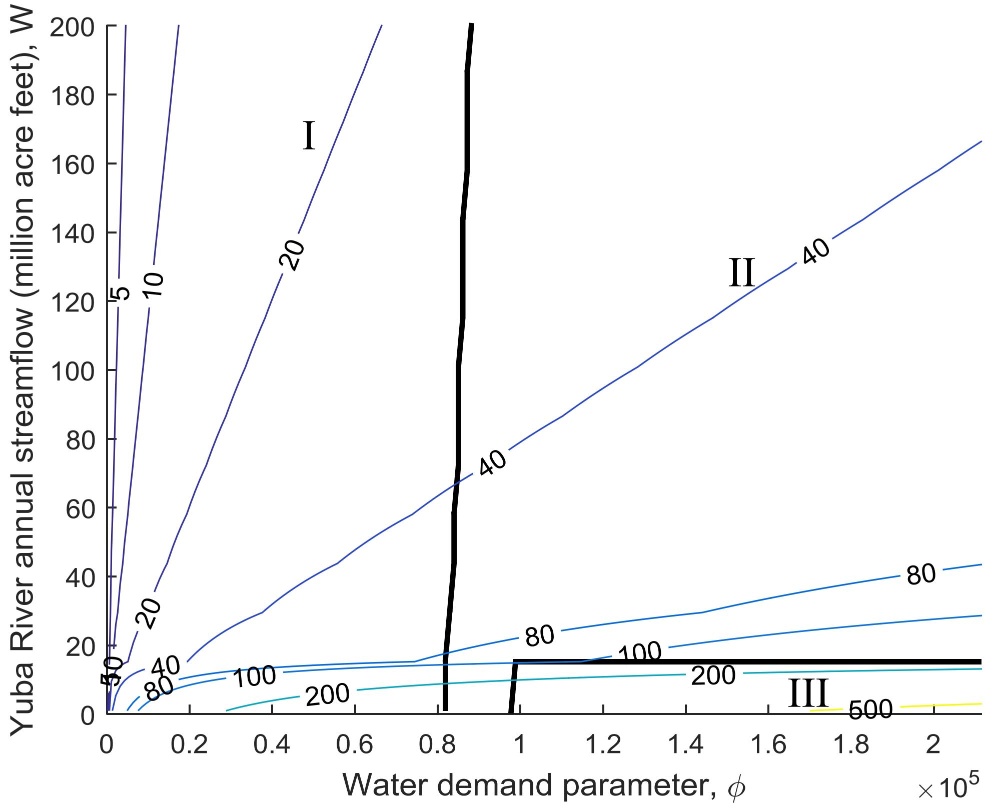

Figure 7. Critical private adaptation threshold for a backward-looking farmer that bases expectations of water supply on historic streamflow conditions in the Yuba River

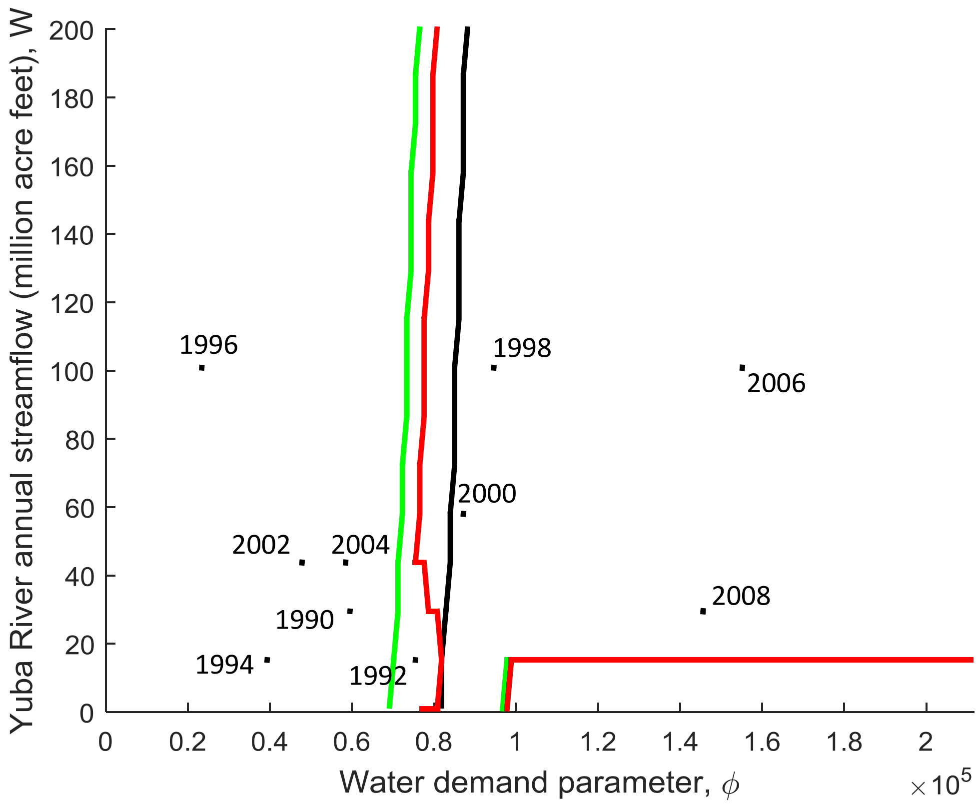

Figure 8. Influence of climate change expectations on water-saving irrigation investment thresholds. Black line is the investment threshold for a backward-looking farmer that bases future expectations on historic conditions. Red line is the investment threshold for a forward-looking farmer that is ambiguity neutral. Green line is the investment threshold for a farmer that is ambiguity averse.

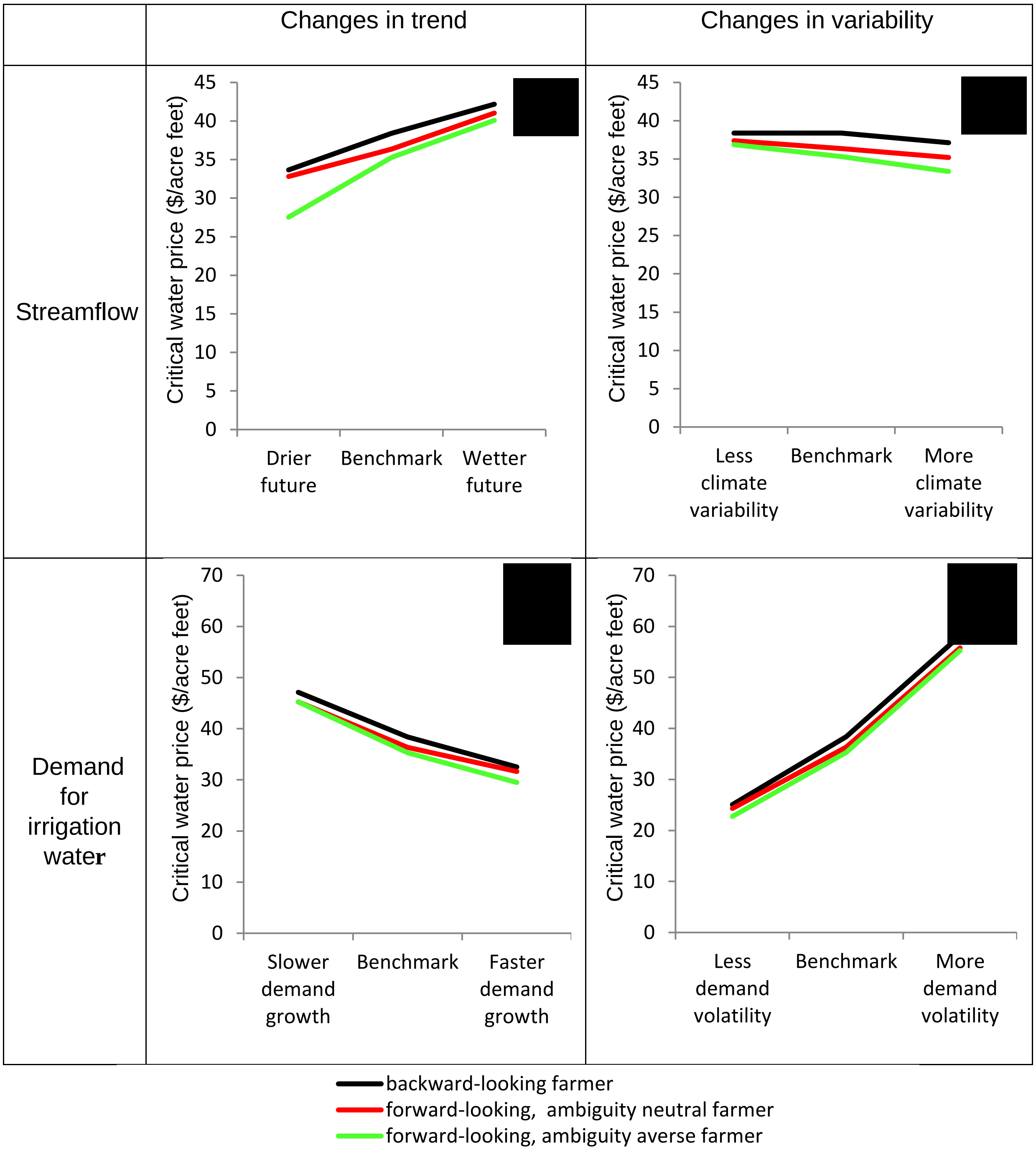

Figure 9. Effect of trend and variability in streamflow and market for irrigation water on the critical water price that triggers water conservation under normal streamflow conditions (*W*=70 million annual acre feet)

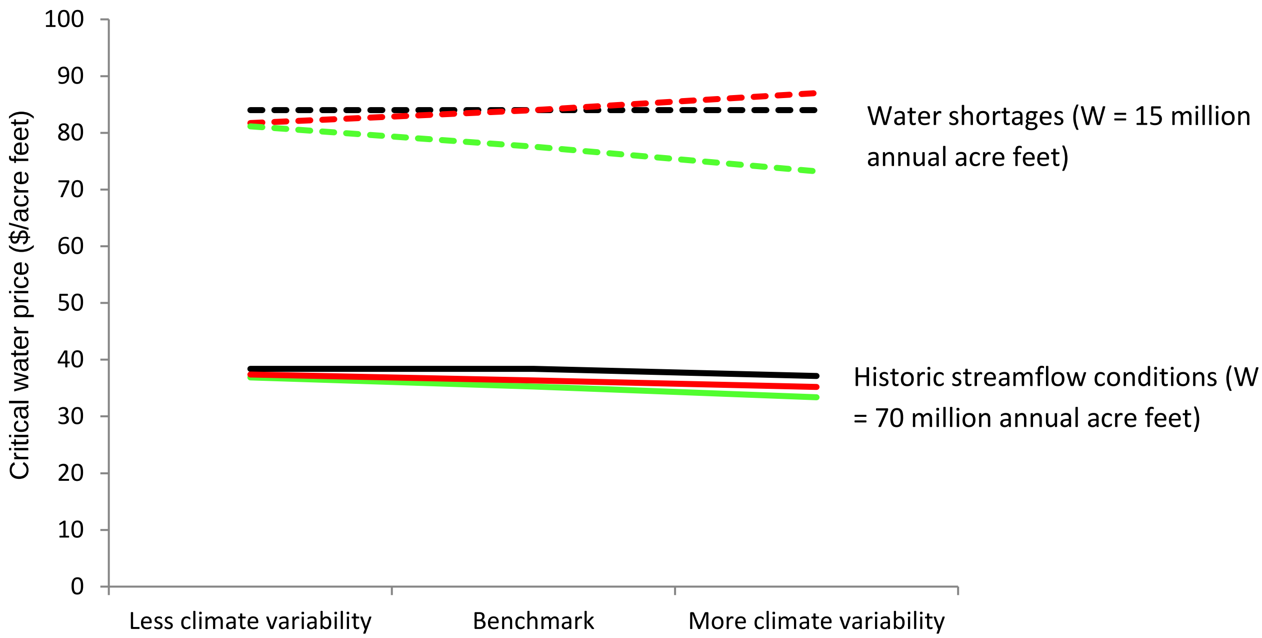

Figure 10. Influence of climate variability during normal streamflow conditions and water shortages

References

Albouy, D., et al. 2016. "Climate Amenities, Climate Change, and American Quality of Life." *Journal of the Association of Environmental and Resource Economists* 3:205-246.

Arrow, K.J., and A.C. Fisher. 1974. "Environmental Preservation, Uncertainty, and Irreversibility." *The Quarterly Journal of Economics* 88:312-319.

Balikcioglu, M., P.L. Fackler, and R.S. Pindyck. 2011. "Solving optimal timing problems in environmental economics." *Resource and Energy Economics* 33:761-768.

Berck, P., and G. Helfand. 1990. "Reconciling the von Liebig and differentiable crop production functions." *American Journal of Agricultural Economics* 72:985-996.

Bhaduri, A., and U. Manna. 2014. "Impacts of water supply uncertainty and storage on efficient irrigation technology adoption." *Natural Resource Modeling* 27:1-24.

Bosello, F., C. Carraro, and E. De Cian. 2010. "Climate policy and the optimal balance between mitigation, adaptation and unavoided damage." *Climate Change Economics* 1:71-92.

Brekke, L., et al. 2013. "Downscaled CMIP3 and CMIP5 climate and hydrology projections: Release of downscaled CMIP5 climate projections, comparison with preceding information, and summary of user needs." *US Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, Colorado, USA.*

Brown, P. (2008) "Flood vs. Pivot irrigation for Forage Crops: What are the Advantages and Disadvantages?" In *Proceedings, California Alfalfa & Forage Symposium and Western Seed Conference, San Diego, CA.*

Burton, I. 1997. "Vulnerability and adaptive response in the context of climate and climate change." *Climatic Change* 36:185-196.

Carey, J.M., and D. Zilberman. 2002. "A model of investment under uncertainty: modern irrigation technology and emerging markets in water." *American Journal of Agricultural Economics* 84:171-183.

Chambwera, M., et al. (2014) "Economics of adaptation." In C.B. Field,V.R. Barros,D.J. Dokken,K.J. Mach,M.D. Mastrandrea,T.E. Bilir,M. Chatterjee,K.L. Ebi,Y.O. Estrada,R.C. Genova,B. Girma,E.S. Kissel,A.N. Levy,S. MacCracken,P.R. Mastrandrea, and L.L. White eds. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press, pp. 945-977.

Costinot, A., D. Donaldson, and C. Smith. 2016. "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world." *Journal of Political Economy* 124:205-248.

De Bruin, K.C., R.B. Dellink, and R.S. Tol. 2009. "AD-DICE: an implementation of adaptation in the DICE model." *Climatic Change* 95:63-81.

Fisher, A.C., and S.J. Rubio. 1997. "Adjusting to climate change: Implications of increased variability and asymmetric adjustment costs for investment in water reserves." *Journal of Environmental Economics and Management* 34:207-227.

Flato, G., et al. (2013) "Evaluation of Climate Models." In T.F. Stocker,D. Qin,G.-K. Plattner,M. Tignor,S.K. Allen,J. SBoschung,A. Nauels,Y. Xia,V. Bex, and P.M. Midgley eds. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press, pp. 741-866.

Gersonius, B., et al. 2013. "Climate change uncertainty: building flexibility into water and flood risk infrastructure." *Climatic Change* 116:411-423.

Gilboa, I., and D. Schmeidler. 1989. "Maxmin expected utility with non-unique prior." *Journal of mathematical economics* 18:141-153.

Golub, A., D. Narita, and M.G. Schmidt. 2014. "Uncertainty in integrated assessment models of climate change: Alternative analytical approaches." *Environmental Modeling & Assessment* 19:99-109.

Hallegatte, S., and P. Dumas. 2009. "Can natural disasters have positive consequences? Investigating the role of embodied technical change." *Ecological Economics* 68:777-786.

Heal, G., and B. Kriström. 2002. "Uncertainty and climate change." *Environmental and Resource Economics* 22:3-39.

Henry, C. 1974. "Investment Decisions Under Uncertainty: The "Irreversibility Effect"." *The American Economic Review* 64:1006-1012.

Knutti, R., and J. Sedláček. 2013. "Robustness and uncertainties in the new CMIP5 climate model projections." *Nature Climate Change* 3:369-373.

Kousky, C., E.F. Luttmer, and R.J. Zeckhauser. 2006. "Private investment and government protection." *Journal of Risk and Uncertainty* 33:73-100.

Letey, J. (1991) "Crop-water production function and the problems of drainage and salinity." In *The economics and management of water and drainage in agriculture.* Springer, pp. 209-227.

Lo, A.W., and J. Wang. 1995. "Implementing option pricing models when asset returns are predictable." *The Journal of Finance* 50:87-129.

Lundquist, J.D., D.R. Cayan, and M.D. Dettinger. 2004. "Spring onset in the Sierra Nevada: When is snowmelt independent of elevation?" *Journal of Hydrometeorology* 5:327-342.

Margulis, S., et al. 2010. "Economics of adaptation to climate change: Synthesis report." *World Bank Climate Change Synthesis Report*.

Marten, A.L., and C.C. Moore. 2011. "An options based bioeconomic model for biological and chemical control of invasive species." *Ecological Economics* 70:2050-2061.

Maurer, E.P. 2010. "The utility of daily large-scale climate data in the assessment of climate change impacts on daily streamflow in California."

Milly, P.C.D., et al. 2008. "Stationarity Is Dead: Whither Water Management?" *Science* 319:573-574.

Narita, D., and M.F. Quaas. 2014. "Adaptation to climate change and climate variability: Do it now or wait and see?" *Climate Change Economics* 5:1450013.

Null, S.E., J.H. Viers, and J.F. Mount. 2010. "Hydrologic response and watershed sensitivity to climate warming in California's Sierra Nevada." *PLoS One* 5:e9932.

Olmstead, A.L., and P.W. Rhode. 2011. "Adapting North American wheat production to climatic challenges, 1839–2009." *Proceedings of the National Academy of Sciences* 108:480-485.

Olmstead, S.M., and R.N. Stavins. 2009. "Comparing price and nonprice approaches to urban water conservation." *Water Resources Research* 45.

Peterson, D.H., I. Stewart, and F. Murphy. 2008. "Principal hydrologic responses to climatic and geologic variability in the Sierra Nevada, California." *San Francisco Estuary and Watershed Science* 6.

Saphores, J.D. 2004. "Environmental Uncertainty and the Timing of Environmental Policy." *Natural Resource Modeling* 17:163-190.

Sturm, M., et al. 2016. "Using an option pricing approach to evaluate strategic decisions in a rapidly changing climate: Black–Scholes and climate change." *Climatic Change*:1-13.

Taylor, K.E., R.J. Stouffer, and G.A. Meehl. 2012. "An overview of CMIP5 and the experiment design." *Bulletin of the American Meteorological Society* 93:485-498.

Tindula, G.N., M.N. Orang, and R.L. Snyder. 2013. "Survey of irrigation methods in California in 2010." *Journal of Irrigation and Drainage Engineering* 139:233-238.

Treasury, H. 2009. "Accounting for the effects of climate change: supplementary green book guidance." *HM Treasury, London*.

Venkatesh, B.N., and B.F. Hobbs. 1999. "Analyzing investments for managing Lake Erie levels under climate change uncertainty." *Water Resources Research* 35:1671-1683.

Wang, W., and B.A. McCarl. 2013. "Temporal investment in climate change adaptation and mitigation." *Climate Change Economics* 4:1350009.

Woodward, M., Z. Kapelan, and B. Gouldby. 2014. "Adaptive flood risk management under climate change uncertainty using real options and optimization." *Risk Analysis* 34:75-92.

Wright, E.L., and J.D. Erickson. 2003. "Climate variability, economic adaptation, and investment timing." *International Journal of Global Environmental Issues* 3:357-368.

Yates, D., et al. 2005. "WEAP21—A demand-, priority-, and preference-driven water planning model: part 1: model characteristics." *Water International* 30:487-500.

Young, C.A., et al. (2009) "Modeling the hydrology of climate change in California's Sierra Nevada for subwatershed scale adaptation1." In., Wiley Online Library.