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Climate risk management in agriculture using alternative electricity and water resources: a stochastic programming framework

Erick C. Jones Jr.[1] · **Benjamin D. Leibowicz**[2]

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Abstract
Climate change, extreme weather events, and water scarcity have severely impacted the agricultural sector. Under scarce conventional water supplies, a farm faces a decision between reducing production through deficit irrigation and leveraging alternative water and energy resources to continue producing large quantities of crops and these investments would have to be balanced against an unknown climate. Therefore, we develop a framework for farm investment decisions structured as a two-stage stochastic quadratically constrained linear program that maximizes farm profit over a 25-year period while considering an uncertain future climate and the costs of investing and operating various electricity and water technologies. We create four representative climate futures and two climate probability distributions that represent different beliefs that the decision maker might have about the likelihood of each climate scenario occurring. Then, we compare four solutions where decisions are made on information ranging from perfectly knowing the climate and weather to only the average precipitation. Our results show that expected profit and crop yield heavily depend on a decision maker's given climate probability distributions. Aggressively preparing for an extreme climate can cause significant losses if a more moderate climate is realized. Furthermore, given a future climate, year-to-year weather variability can also corrode the potential cost savings from investing in alternative resources. The insights from this framework can help agricultural decision makers determine how to address climate uncertainty, water scarcity, and to a limited degree weather variability via investments in alternative water and electricity resources that can help improve resilience and fortify profits.

Keywords Climate risk management · Water scarcity · Stochastic programming · Food–energy–water systems · Desalination · Agriculture

1 Introduction

As climate change intensifies and essential resources like water become more scarce, planning for these risks has become essential. To address these needs, we create a two-stage stochastic programming framework that makes first-stage investment decisions for alternative water and electricity capacity additions under climate uncertainty and second-stage operational decisions after the uncertainty is realized. In this work, we apply this framework to an agricultural setting where climate uncertainty and water scarcity present risks not just for farm owners but for everyone. Therefore, the main objectives of this case study are to investigate how a farm can manage the risk of climate uncertainty, how water scarcity affects its operations, and to examine how well this framework performs at advising a decision maker on the investments they can make to mitigate both climate uncertainty and resource scarcity.

Prolonged droughts associated with climate change and increased water withdrawals at unsustainable rates, from sources like aquifers, have placed a significant strain on water resources for both municipal and agricultural uses. In fact, some farmers have found it more profitable to sell water rather than use it to grow crops (Sengupta 2021). As the population grows, there will be less water from traditional

✉ Erick C. Jones Jr.
erick.jones@uta.edu

Benjamin D. Leibowicz
bleibowicz@utexas.edu

1 Industrial, Manufacturing, and Systems Engineering, The University of Texas at Arlington, Woolf Hall Room 420X, 500 West 1st St, Arlington, TX 76019, USA

2 Operations Research and Industrial Engineering, The University of Texas at Austin, ETC 5.128D, 204 E. Dean Keeton St., C2200, Austin, TX 78712, USA

sources available for agriculture. However, there are unconventional sources of water that could become profitable inputs to agricultural production when conventional water or crop prices increase. These unconventional water sources can be far below ground and/or have higher concentrations of contaminants like salt. Finding cost-effective ways to access these unconventional water sources and then applying treatment as necessary to help make agricultural production more robust in the face of climate and weather uncertainties is essential to preserve increasing scarce water resources.

In this paper, we propose a model that maximizes profit by balancing crop yield, water treatment and pumping costs, and the costs of the electricity required to pump and treat the water. Integrated food–energy–water systems allow for the flexibility to take advantage of the cost savings and resources that would not be available if a farm relied only on centralized resources. Under scarce conventional water supplies, a farm faces a decision between reducing production through deficit irrigation and leveraging alternative water resources to continue producing large quantities of crops. Importantly, leveraging alternative water resources typically requires additional energy inputs and this energy could be obtained from the grid or from distributed energy resources. These investments would have to be balanced against an unknown climate and weather where the amount of precipitation available could vary wildly from year-to-year. Therefore, we develop a framework for farm investment decisions structured as a two-stage stochastic quadratically constrained linear program (QCLP) that maximizes farm profit over a 25-year period while considering an uncertain future climate and the costs of investing and operating various electricity and water technologies.

To investigate our main objectives, we compare solutions where the weather and climate are known before an investment decision is made (Perfect Information), the climate but not the weather are known before the investment decisions (Known Climate Unknown Weather), investment decisions are made by hedging all possible climates and weathers (Stochastic), and investment decisions are made based on the average climate (Expected Value).

To investigate different climate futures we create four representative climates—Dry, Dry-Moderate, Moderate, and Wet—that inform a Markov chain that produces annual precipitation values that correlate with a given climate. For example, the Dry climate is more likely to produce low precipitation years and the Wet climate is more likely to produce high precipitation years.

Furthermore, we consider two different climate probability distributions—Equally Probable and Dry Most Likely—that represent different beliefs that the decision maker might have about the likelihood of each climate scenario occurring. The Equally Probable probability represents the belief all climates are equally likely and the Dry Most Likely probability represents the belief that the Dry climate is the most likely. The decision maker needs these climate probability distributions in order to make an investment decision.

Our model shows that climate uncertainty is the biggest factor affecting potential profit and weighting your investment based on a climate that does not occur can severely impact profits. Optimally hedging investment decisions can balance this downside risk, but when the possible climates trend toward a moderate climate, optimally hedging provides little benefit over simply preparing for the average possible climate. Nonetheless, even though climate uncertainty is the biggest factor affecting profit, the year-to-year weather variability for a given climate can also cause significant swings in profit. The variability in precipitation from year-to-year can erode profits by having an alternative water and/or electricity investment be undersized one year and oversized another. Understanding how these uncertainties can affect a farm's optimal investment decisions and by extension their profit is vastly important, and this model provides a framework to provide these insights.

The remainder of the paper is organized as follows. Section 2 reviews relevant literature on climate risk management, food–energy–water modeling, and crop production functions. Section 3 details the framework formulation, solution types, model parameterization, and the climate and climate probability distribution calculations. Section 4 details the results of the study and Sect. 5 summarizes the most significant findings.

2 Background

2.1 Climate risk management

The main driving force for this work is understanding how climate uncertainty and accompanying resource scarcity will impact agricultural operations and what can be done to mitigate that. This subsection addresses the literature related to climate uncertainty.

As climate change takes hold, extreme weather events and resource scarcity are expected. These uncertainties will affect decision makers who make a wide variety of decisions from energy decisions (Leibowicz 2018), climate policy (Moreno-Cruz and Keith 2013), and economics via carbon pricing (Nordhaus 1992).

In the agricultural setting, climate change has already impacted the livelihood of farmers in the Ecuadorian Andes (Blackmore et al. 2021), the Northern Ethiopian Highlands (Adamseged et al. 2019), and Sub-Saharan Africa (Guido et al. 2020). As a result, how farmers should respond to these climate risks is becoming more important.

Anderson and Kyveryga (2016) illustrated how long-term climate data and observations could be used to quantify climate risks. Wheeler and Lobley (2021) surveyed UK farmers to determine how and/or if they were adapting to increased climate risk and if the creation of farmer specific tools would help farmers adapt to climate risks. Laureti et al. (2021) applied a spatial stochastic frontier model to investigate in Southern Italy if their was spatial heterogeneity in crop water efficiency and to encourage policy makers to consider more water efficient crop choices like diffusion of crops more suitable to water scarcity. We created the framework outlined in this work to be an adaptable tool that farmers could use to access and prepare for climate risk.

In Texas, the uncertainty in water planning presents the biggest problem for the heavily agricultural state. Werner and Svedin (2017) found that the Texas water plan does not adequately prepare for climate change. Furthermore, Jones and van Vliet (2018) note that water scarcity in Texas is not only a result of increasing water withdrawals, but of increasing water salinity. Nonetheless, researchers have increasingly investigated how to adapt to climate risks in Texas, for example (Shrum et al. 2018) investigated how a Texas ranch could adapt to water scarcity to maintain protein production. Nielsen-Gammon et al. (2020) provided general insights into how different drought and climate projections could help Texas water planners prepare for a climate uncertain future. The same water uncertainty and potential scarcity that affects the water supply also directly affects crop growth for farmers. This study tests our framework by using a water constrained farm in Texas as a case study.

This work expands upon the climate change management literature by creating a framework that allows farmers to tailor a strategy to mitigate climate risk and resource scarcity. This framework investigates the how different climate futures could affect farmers via the investment decisions they will have to make in the present and how those investment decisions and the climate will affect their operational decisions in the future.

2.2 Food–energy–water modeling

Our model investigates three distinct sectors—food, energy, and water—that each have their own distinct modeling literature. As drought, climate change, and urbanization stress fresh water sources, alternative water research is becoming especially important.

Alternative water sources like brackish water are popular alternatives to groundwater (LBG-Guyton Associates 2003). Furthermore, research, like (Blinco et al. 2017) which investigated how to optimize the operation and design of systems that use alternative water sources like wastewater treatment and desalination, is another area of interest. However, the work by Arroyo and Shirazi (2012), which detailed the brackish water treatment facilities in Texas and their costs, provides the technological foundation of our work.

Nonetheless, as the operations of food, energy, and water systems become more intertwined, so does the modeling literature. Therefore, for the remainder of this subsection we investigate the literature related to food–energy–water modeling that can help us with our own formulation.

There has been a recent trend in research that has investigated how energy and water systems could be designed together to reduce costs or deal with environmental impacts. Jones and Leibowicz (2021) investigated how the co-optimization of community scale distributed water and energy systems could reduce costs and Vitter et al. (2018) investigated how a community scale wastewater treatment plant could be more cost effective than centralized wastewater treatment. Yet, research related to how food, energy, and water could all be designed together has remained sparse.

Nonetheless, after (Heady 1954) developed one of the first uses of linear programming in farming by creating a simple model that maximizes farm profit, modeling farm operations has expanded to not only include the crops, but the technology to get water to the crops and to produce the electricity to power the water systems. Ghasemi (2018) modeled an agricultural microgrid that includes the irrigation water requirements, a water reservoir, an agricultural products packing factory, the lighting load requirements, and other electrical items. Campana et al. (2013) created a dynamic modeling tool of a PV water pumping system that includes a water demand model, a solar PV model, and a pumping system model for quick design and validation. Then Campana et al. (2015) expanded their previous work by modeling how a PV powered pump watering system could be paired with a crop growth model. Zhang et al. (2018) elevated this modeling paradigm further by creating an integrated modeling system that combined a dynamic land ecosystem model, an optimization based economic model, and a regional climate model.

Our model follows this tradition of integrated food–energy–water modeling and expands it by placing an emphasis on optimizing investment decisions under climate uncertainty. However, we take a slight detour from the trends to larger and more integrated systems by limiting our technology choices and keeping the scale to a single farm.

2.3 Crop production functions

Crop functions are empirically determined functions that relate water depth, soil salinity, water salinity and more with crop yield. In order to model crop growth, we need a crop function that can be integrated into our modeling framework. Therefore, in this subsection we examine different crop functions and their uses throughout the literature.

There is a large body of work that seeks to mathematically define the relationship between crop yield and soil water depth for a variety of crops.

Barrett and Skogerboe (1980) compiled a list of different types of crop functions calculated over the years looking at linear functions, non-linear functions, how the timing of water affects growth, and the relationship between yield and evapotranspiration. Zhang and Oweis (1999) investigated the water-yield relationship for wheat in the Mediterranean Region and developed easy to interpret linear and quadratic yield functions. Foster and Brozović (2018) researched how to simulate crop yields based on irrigation and rain by investigating the difference between additive crop yield functions and multiplicative crop yield functions while taking into account water timing. Specifically, they created a crop-water growth model that addresses the disadvantages of the crop-water coefficient model when addressing the timing of water deficits. Smilovic et al. (2016) also modeled a crop coefficient model that takes into account how the timing of watering impacts a crop's yield. They use two coefficients, a crop coefficient and a scarcity index, to correct for timing and location. The end result is what they call a crop kite which relates deficit irrigation to yield while taking into account timing.

However, for this work we sought a crop function that took into account over-watering and salt concentration but didn't actively model water timing to save on complexity. So, we use the model developed by Dinar et al. (1991) which estimated a set of yield production functions using water quantity and quality, soil salinity, and drainage volume.

3 Methodology

3.1 Model formulation

Our framework for farm investment decisions creates a stochastic quadratically constrained linear program (QCLP) to capture the quadratic relationship between crop growth and water inputs. The QCLP maximizes farm profit over a 25-year period. The stochastic QCLP represents a case where a decision maker makes a set of investment decisions before a climate is realized and then makes operation decisions based on that set of investment decisions once the climate is known. We investigate different solution cases, but they all use the same general QCLP formulation, including parameters and variables. The main differences between the solution cases are if the set of investment decisions are fixed or endogenous to the model, if the climate and/or weather is uncertain or not, which climate(s) is (are) being investigated, and what probability is given for each climate to occur in the future. In this section, we outline the model formulation, including parameters, variables, and equations.

Instance input parameters:

I	Set of weather realizations
Y	Set of years (1–25)
ha	Size of farm (hectares [ha])
$price$	Price of crop ($/ton)
c_{aw}	Unit cost of alternative water ($/ha-cm)
c_{iw}	Unit cost of irrigation water ($/ha-cm)
c_{ae}	Investment cost of alternative electricity ($/kW)
c_{ue}	Unit cost of utility electricity ($/kWh)
eu_{aw}	Unit energy use of alternative water (kWh/ha-cm)
eu_{iw}	Unit energy use of irrigation water (kWh/ha-cm)
scw	Salt concentration in water (dS/m)
scs	Salt concentration in soil (dS/m)
iwl	Irrigation water limit (hectares-cm)
gsm	Growing season months
cfs	Capacity factor solar
$mhrs$	Hours in a month
$rain_{i,y}$	Precipitation in weather realization i and year y (ha-cm)

QCLP decision variables:

$capacity^{AW} \in \mathbb{R}_{\geq 0}$	Invested capacity of alternative water (ha-cm)
$capacity^{AE} \in \mathbb{R}_{\geq 0}$	Invested capacity of alternative electricity (kW)
$water^{Total}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of water used (ha-cm) in weather realization i and year y
$water^{IW}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of irrigation water used (ha-cm) in weather realization i and year y
$water^{AW}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of alternative water used (ha-cm) in weather realization i and year y
$elc^{Total}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of electricity used (kWh) in weather realization i and year y
$elc^{AE}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of alternative electricity used (kWh) in weather realization i and year y
$elc^{UE}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of utility electricity used (kWh) in weather realization i and year y
$cy_{i,y} \in \mathbb{R}_{\geq 0}$	Crop yield (tons/ha) in weather realization i and year y
$profit_i \in \mathbb{R}_{\geq 0}$	Profit ($) in weather realization i

3.1.1 Objective function

The framework is driven by profit which is equal to the revenue from selling the crop minus the costs of the water and electricity inputs as shown in Eq. 1.

$$profit = \overbrace{\sum_{i\in I}\sum_{y\in Y} ha * price * cy^{i,y}}^{\text{Revenue}} - \overbrace{capacity^{AW} c_{aw} - \sum_{i\in I}\sum_{y\in Y} water^{IW}_{i,y} c_{iw}}^{\text{Water Cost}} - \overbrace{capacity^{AE} c_{ae} - \sum_{i\in I}\sum_{y\in Y} elc^{UE}_{i,y} c_{ue}}^{\text{Electricity Cost}} \quad (1)$$

3.1.2 Crop yield function

Crop production functions use the relationship between water depth and salinity to predict crop growth. In these crop production functions, crop yield is a function of water depth, water salinity, soil salinity, and in some cases, other variables. In this model, we calculate crop growth every year for every weather realization. Equation 13 in Sect. 3.7 shows the fully parameterized equation.

3.1.3 Investment decision equations

Each optimization problem makes a single alternative water investment decision and a single alternative electricity investment decision regardless of the number of weather realizations. This replicates how a decision maker would have to make a single set of investment decisions over a wide range of possibilities. How much capacity the decision maker decides to invest in governs how many alternative resources are available for a given year as shown in Eqs. 2 and 3.

$$capacity^{AW} \geq water^{AW}_{i,y}, \forall i \in I, \forall y \in Y \quad (2)$$

$$capacity^{AE} * cfs * mhrs * gsm \geq elc^{AE}_{i,y}, \forall i \in I, \forall y \in Y \quad (3)$$

3.1.4 Operational decision equations

The farm decision maker decides how much groundwater and/or alternative water to provide for his crops to supplement the exogenously specified precipitation and how to supply the power needed for those water sources either through a centralized utility or installed alternative electricity capacity. These decisions are governed by balance equations which ensure that the endogenously specified demands for water and electricity are satisfied. These balance equations are encoded in Eqs. 4, 5, and 6. Note, precipitation cannot be controlled by the farm and any rain must count toward the crop production function; this is enforced by Eq. 7. Also, to simulate future resource constraints, irrigation water is limited, as shown in Eq. 8.

$$rain_{i,y} + water^{AW}_{i,y} + water^{IW}_{i,y} \geq water^{Total}_{i,y} \forall i \in I, \forall y \in Y \quad (4)$$

$$elc^{AE}_{i,y} + elc^{UE}_{i,y} \leq elc^{Total}_{i,y} \forall i \in I, \forall y \in Y \quad (5)$$

$$water^{AW}_{i,y} eu_{aw} + water^{IW}_{i,y} eu_{iw} \geq elc^{Total}_{i,y} \forall i \in I, \forall y \in Y \quad (6)$$

$$water^{AW}_{i,y} eu_{aw} + water^{IW}_{i,y} eu_{iw} \geq elc^{Total}_{i,y} \forall i \in I, \forall y \in Y \quad (7)$$

$$water^{IW}_{i,y} \leq iwl, \forall y \in Y \quad (8)$$

3.2 Model solution types

We analyze the farm's decisions using the three main stochastic programming solutions: Perfect Information, Expected Value, and Stochastic. We also develop a solution where the climate is known like the Perfect Information scenario but the weather is not and call this solution Known Climate Unknown Weather.

3.2.1 Stochastic solution formulation

Equation 9 shows the general two-stage stochastic program formulation (Leibowicz 2018) which represents the Stochastic solution in this study.

$$\begin{aligned} \max_{x,(y_\omega)\omega\in\Omega} z^{SS} &= c^T x + \mathbb{E}_\omega d^T_\omega y_\omega \\ s.t. \quad Ax &= b \\ B_\omega x + C_\omega y_\omega = f_\omega &\quad \forall \omega \in \Omega \\ x, y_\omega \geq 0 &\quad \forall \omega \in \Omega \end{aligned} \quad (9)$$

In this formulation, the first stage objective function coefficients (the c vector) which in our problem represent the costs of investment and the first stage constraints (the A matrix and the b vector) which in our problem represent the capacity limits of those investments are known with certainty. The second-stage objective function coefficients (the d_ω vector) and the second-stage constraints (the B_ω and C_ω matrices and the f_ω vector) are uncertain when the first-stage decisions (the x vector) are made, but are known when the recourse decisions (the y_ω vector) which in our problem represent the operational decisions are determined. The ω subscripts, which in this study represent a weather vector, symbolize that the parameters and decision variables represent a subset of our representation of the world which in this study is the set of all weather realizations for all climates ($\omega \in \Omega$). The objective is then maximized over all states of our representative world, where the probability of a given state is $p(\omega)$. The single objective function (z^{SS}) produced from the Stochastic solution is the objective value.

The Stochastic Solution represents a feasible decision set that optimally hedges for a given set of weather realizations. Optimally hedging for all possible weather realizations will at worse perform the same as the Expected Value solution and should perform better. The difference between the objective value of the Stochastic solution (z^{SS}) and the expected value of the Expected Value solutions (z^{EV}) is called the Value of the Stochastic Solution (VSS). However, the Stochastic solution will at best perform as well as the Perfect Information solution and likely significantly worse. The difference between the expected value of the Perfect Information solutions (z^{PI}) and the Stochastic Solution (z^{SS}) is called the Expected Value of Perfect Information (EVPI).

3.2.2 Perfect information solution formulation

The Perfect Information solutions each solve an optimization problem for a single weather realization (ω). Each solution produces a set of investment decisions (x_ω) and a set of operational decisions (y_ω) that are based on that solution's weather realization. This contrasts with the Stochastic solution, where the solution produces one set of investment decisions for all the weather realizations and not a solution for a single weather realization like a Perfect Information solution. After a Perfect Information solution is created for each weather realization, a weighted average of the objective values for each solution (z_ω) are used to produce the expected value of the Perfect Information solutions (z^{PI}). The mathematical formulation of a Perfect Information solution and the expected value of the Perfect Information solutions are shown in Eq. 10.

$$\begin{aligned} \max_{x_\omega, y_\omega} z_\omega &= c^T x_\omega + d_\omega^T y_\omega, quad \forall \omega \in \Omega \\ z^{PI} &= \mathbb{E}(z_\omega) = \sum_{\omega \in \Omega} p(\omega) z_\omega \end{aligned} \tag{10}$$

The expected value of the Perfect Information solutions represents the maximum expected profit from a given set of climates and weather realizations. This maximum expected profit is then used as a baseline to compare how the other solutions perform and to determine the EVPI.

3.2.3 Expected value solution formulation

The Expected Value solution makes a single set of investment decisions ($x_{\bar{\omega}}$) based on the average climate ($\bar{\omega}$) rather than by taking into account all the possible combinations of weather and climate like the Stochastic solution. Then, that single set of investment decisions ($x_{\bar{\omega}}$) is used to determine the operational decisions (y_ω) for each weather realization (ω). After an Expected Value solution is created for each weather realization, a weighted average of the objective values for each solution (z_ω) is used to produce the expected value of the Expected Value solutions (z^{EV}). The mathematical formulation of an Expected Value solution, and the expected value of the Expected Value solutions are shown in Eq. 11.

$$\begin{aligned} \max_{x_{\bar{\omega}}, y_\omega} z_\omega &= c^T x_{\bar{\omega}} + d_\omega^T y_\omega, \quad \forall \omega \in \Omega \\ z^{EV} &= \mathbb{E}(z_\omega) = \sum_{\omega \in \Omega} p(\omega) z_\omega \\ s.t. \quad x_{\bar{\omega}} &\in argmin \quad c^T x + d_{\bar{\omega}} y_{\bar{\omega}} \\ \bar{\omega} &= \mathbb{E}(\omega) = \sum_{\omega \in \Omega} p(\omega)\omega \end{aligned} \tag{11}$$

The Expected Value solution illustrates naïve investment decision making where a decision maker does not take into account all the possible climates and weather realizations and instead only makes a decision based on an average climate. This Expected Value solution can then be compared to a Stochastic solution that makes an investment decision by optimally hedging on the complete set of possible climate and weather outcomes.

3.2.4 Known climate unknown weather solution formulation

The Value of Perfect Information, while informative, represents a solution that is impossible to perform as well as, where not only would you know the climate for the next 25 years but the exact weather and rainfall for the next 25 years as well. While the future climate and weather are both uncertain, climate can be predicted over long time horizons including the 25 year time horizon that the investment decision will affect making it more "knowable" than the weather and by extension seasonal precipitation which can only be predicted for a few weeks (Palmer 2000; Bauer et al. 2015; Parker 2010; Slingo and Palmer 2011). We postulate that a metric where the climate for the next 25 years is known but every weather fluctuation is not would provide a better point of comparison for this particular model. Therefore, we created the Known Climate Unknown Weather solution where even if we perfectly understand climate change, there will still be weather and by extension seasonal precipitation variability across years that cannot be perfectly predicted.

A Known Climate Unknown Weather solution makes a single set of investment decisions ($x_{\omega'}$) and operational decisions (y_ω) based on the set of weather realizations ($\omega \in \omega'$) in a given climate (ω'). After a Known Climate Unknown

Weather solution is created for each climate, a weighted average of the objective values for each solution ($z_{\omega'}$) is used to produce the expected value of the Known Weather Unknown Climate solutions (z^{KCUW}). The mathematical formulation of a Known Climate Unknown Weather solution, and the expected value of the Known Climate Unknown Weather solutions are shown in Equation 12.

$$\begin{aligned} \max_{x_{\omega'},(y_\omega)\omega\in\omega'} z_{\omega'} = c^T x_{\omega'} + \mathbb{E}_\omega d_\omega^T y_\omega \quad \forall\omega' \in \Omega \\ s.t. \quad Ax_{\omega'} = b \\ B_\omega x_{\omega'} + C_\omega y_\omega = f_\omega \quad \forall\omega \in \omega' \\ x_{\omega'}, y_\omega \geq 0 \quad \forall\omega \in \omega' \\ z^{KCUW} = \mathbb{E}(z_{\omega'}) = \sum_{\omega\in\omega'} p(\omega') z_{\omega'} \end{aligned} \tag{12}$$

Like the Stochastic solution, the Known Climate Unknown Weather solution represents a feasible decision set that optimally hedges for a given set of weather realizations; however, the Known Climate Unknown Weather hedges based on the weather realizations of a single known climate. Therefore, the Known Climate Unknown Weather solution will at worse perform the same as the Stochastic solution and at best perform as well as the Perfect Information solution. We call the difference between the objective value of the Stochastic solution (z^{SS}) and the expected value of the Known Climate Unknown Weather solutions (z^{KCUW}) the Expected Value of Known Climate (EVKC) and the difference between the expected value of the Perfect Information solutions (z^{PI}) and the expected value of the Known Climate Unknown Weather solutions (z^{KCUW}) the Expected Value of Known Weather (EVKW).

3.3 Climate probability distributions

The climate probability distributions are designed to help us address our primary research questions and hypotheses. Specifically, we are interested in understanding how the probabilities of a range of climates affect investment decisions in alternative energy and water, how those investment decisions perform in different climate realizations, both predicted and not, and how the variation of weather realizations in a given climate affects profit.

The climate probability distribution is also used to create the appropriate number of weather realizations. For example, the Equally Probable climate probability has 1000 weather realizations from each climate totaling 4000 samples. The Dry Most Likely has 2400 weather realizations from the Dry Climate, 1000 from the Dry-Moderate climate, 400 from the Moderate climate, and only 200 weather realizations from the Wet climate for a total of 4000 samples. The climate probability distributions and their abbreviations are listed below.

- Equally Probable (EP)—where all four climates are equally likely to occur.
- Dry Most Likely (DML)—where the Dry climate is most likely to occur (60% chance) and where the Dry-Moderate, Moderate, and Wet climates have a 25%, 10%, and 5% chance of occurrence, respectively. These climate probabilities reflect researchers' expectations that the future climate of Texas will be drier than it is at present (Nielsen-Gammon et al. 2020)

3.4 Climates and the weather generation Markov chain

We define four distinct climates that produce yearly weather realizations presented as annual precipitation values. The four climates are Dry, Dry-Moderate, Moderate, and Wet. The Wet climate has the highest probability for a high precipitation year followed by the Moderate, Dry-Moderate, and Dry climates in that order.

Each climate is defined by a Markov chain that generates a weather realization and by extension an annual precipitation value for each year. Table 1 shows the probability of an annual precipitation value for a given climate, which corresponds to the Markov chain's stationary distribution.

Furthermore, each Markov chain generator can be run multiple times to represent numerous possible weather samples. Because of the stochastic nature of these Markov chains, samples for a given climate can have significantly different weather realizations. To ensure that the objective values for the solutions and any subsets provide tight confidence intervals, we run 4000 samples for each solution and each subset represents between 200 and 2400 samples. Table 2 illustrates the distribution statistics of the climates for the Equally Probable solutions where each climate Markov chain is sampled 1000 times.

Table 1 Probability of a given value of annual precipitation in inches by climate

Climate	5 inches (%)	15 inches (%)	30 inches (%)	45 inches (%)	60 inches (%)
Dry	20	50	25	5	0
Dry-moderate	5	25	55	10	5
Moderate	20	20	20	20	20
Wet	0	5	20	45	30

Table 2 Annual precipitation distribution statistics by climate

Climate	1st quartile (inches)	Median (inches)	Mean (inches)	3rd quartile (inches)
Dry	15	15	18.3	30
Dry-moderate	15	30	27.93	30
Moderate	15	30	30.96	45
Wet	45	45	45.09	60

3.5 Estimators and estimation methods

To solve the stochastic problems listed in Sect. 3.2 with the climate probability distributions listed in Sect. 3.3 we apply the sample average approximation (SAA) method, a Monte Carlo simulation-based approach to solve discrete stochastic optimization problems (Kleywegt et al. 2006). Using this method, we sample the given probability distributions to produce a set of the only uncertain quantity in the formulation, the parameter vector $rain_i$—a vector of $rain_{i,y}$ values for 25 years. Then we use the generated sample vectors of $rain_i$ to solve their own corresponding optimization problems (one sample vector per optimization problem) as described in previous sections. Since, each stochastic program is a function of a set of decision variables and a set of parameters including the uncertain parameters $rain_{i_y}$, our estimator is the average value of the all the objective functions produced from its own sample vector of $rain_i$. The estimator, denoted by z_ω, estimates the true optimal solution for each solution type. This estimation method produces a good estimator of the true optimal solution and tight error bounds as shown in the results. Furthermore, since the $rain_{i,y}$ values are the only uncertain parameters and are given by an outside probability distribution which cannot be influenced by any other parameters the assumption of exogeneity holds.

3.6 Technologies

To keep the model limited in size, the decision maker can only choose between two technologies for electricity and two technologies for water. The alternative water technology is a reverse osmosis system which takes brackish water with a total dissolved solid (TDS) concentration up to 3.5 g/L—which would include the majority of Texas brackish water resources (LBG-Guyton Associates 2003). The decision maker can also choose to irrigate via a groundwater source which requires electricity for the pumps as outlined in Table 3; however, the amount of groundwater available for use is limited to simulate water scarcity.

The alternative electricity technology is photovoltaic solar (solar PV), where the decision maker decides what size solar farm to invest in. The costs, as shown in Table 3, include installation, inverters, and other ancillary equipment needed for a solar farm installation. And if the decision maker does not wish to invest in alternative electricity, the decision maker can simply choose to purchase electricity from the utility for a conservatively low price of $ 0.08/kWh.

We assume that the pumping system to retrieve and distribute water, brackish or fresh, already exists and that the irrigation system has negligible water losses. Effective precipitation can be significantly lower than actual precipitation and is a function of the evapotranspiration rate of the crop, the amount of precipitation and many other factors including the genetic makeup of the crop (Masoner et al. 2000; Dastane 1978; Sharma et al. 2019). To simplify the model, we define the exogenously defined precipitation as effective precipitation or the amount of precipitation that is utilized by the crop for growth.

3.7 Performance and cost data

Table 3 reports the performance and cost assumptions for each technology and parameter in the model, including operational energy use. Equation 13 shows the quadratic crop

Table 3 Main performance and cost assumptions for technologies and a documentation of data sources

Technology/parameter	Capital costs	O&M costs	Energy use	Other	Source
Utility electricity	–	$ 0.08/kWh	–		City of Austin (2019)
Solar	$ 1500/kW	–	0.30 capacity factor		Fu et al. (2018)
Groundwater	–	$7/acre-in	1 kWh/kGal		Amosson et al. (2019), New (2019)
Desalination	$ 0.40/kGal		6.5 kWh/m^3		LBG-Guyton Associates (2003), Arroyo and Shirazi (2012), Garg and Joshi (2015)
Farm size				200 hectares	Texas Department of Agriculture (2021)
Price of wheat				$ 200/ton	USDA Market News (2021)
Salt concentration water				1.0 dS/m	Dinar et al. (1991)
Salt concentration soil				2.0 dS/m	Dinar et al. (1991)
Irrigation water limit				0.5 acre-ft/acre/yr	United States Department of Agriculture (2017)

production for wheat from Dinar et al. (1991) to model crop growth in this model.

$$
\begin{aligned}
cy^{i,y} \leq -3.350 + 0.2064 * water_{i,y}^{Total} - 0.0014 * water_{i,y}^{Total} * water_{i,y}^{Total} + \\
-0.071 * water_{i,y}^{Total} * scw + 0.033 * water_{i,y}^{Total} * scs + 3.555 * scw + \\
2.326 * scw^2 - 2.031 * scs + 0.823 * scs^2 - 2.754 * scw * scc, \quad \forall i \in I, \forall y \in Y
\end{aligned}
\tag{13}
$$

3.8 Software packages

We generate the random samples using the R programming language's (version 4.1.1) Stats package (version 4.2.0). We build the optimization models using a Python (version 3.8.8) implementation of the Gurobi Modeling and Development Environment (version 9.1.2) and solve them with the Gurobi solver (version 9.1.2).

4 Results

In this section, we present, compare, and discuss results from our scenarios. We begin by examining the differences between the Stochastic (Stoch) solution and the expected objective values for the Perfect Information (PI), Expected Value (EV), and Known Climate Unknown Weather (KCUW) solutions. These comparisons allow us to calculate the Expected Value of Perfect Information (EVPI), the Value of the Stochastic Solution (VSS), the Expected Value of Known Weather (EVKW), and the Expected Value of Known Climate (EWKC). Then we dive deeper by comparing all the Known Climate Unknown Weather solutions to the investment decisions (which remain the same) and the operational decisions of the Stochastic solution for each climate. In this deeper dive we compare how the profit, crop yields, investment decisions, and operations of both water and electricity differ by climate for the Known Climate Unknown Weather and Stochastic solutions.

4.1 Expected objective values and summary statistics

Figure 1 shows the expected objective values for all solutions and Table 4 shows the EVPI, VSS, EVKW, and EVKC. As expected, both climate probability distributions follow the general pattern $z^{PI} \geq z^{KCUW} \geq z^{Stochastic} \geq z^{EV}$ and there is significant value in having perfect information.

However, the value of knowing the climate drives most of the EVPI while knowing the weather adds only a small amount of value. Furthermore, the Expected Value solutions provide virtually the same amount of value as the Stochastic solution despite the sophistication of the Stochastic solution. Although, because of the limited value in knowing the weather compared to the climate, optimally hedging for the weather is expected to provide limited value.

Table 5 shows summary statistics for all solutions. While the standard deviations are relatively large for both profit and crop yield, the 95% confidence intervals for all scenarios, even the ones with only 200 samples, are extremely tight, implying that the expected profits approach the true means.

4.2 Profit comparisons: stochastic vs. known climate unknown weather solutions

After showing the expected objective values in the subsection above, in this subsection we compare the profits of all the Known Climate Unknown Weather solutions and calculate the profits for each climate in the Stochastic solution by first calculating the profit for each weather realization in a given climate by adding the cost of the operation decisions of a weather realization to the fixed investment decisions costs and then averaging the profit of every weather realization in a given climate. We show not just the differences but investigate the reasons for these differences in profit which include average yearly precipitation differences and yearly weather variability.

4.2.1 Drivers of profit variability

Figure 1—which shows the average profit via the bars and bar labels on the left *y*-axis—illustrates that as expected the Wet Climate Known Climate Unknown Weather scenarios produce the highest profits for both climate probability distributions (note in this section we are only comparing the Known Climate Unknown Weather and Stochastic solutions, the Known Climate Unknown Weather solutions still underperform the Perfect Information solutions). And in general, the average yearly precipitation—tracked for each scenario by a black square with its values corresponding to the right *y*-axis—was a reliable predictor of profit for most climates. Also as expected, the Dry climates were the least profitable; however, the Moderate climates have a lower average total profit than the Dry-Moderate climates.

These results add to the findings from the preceding subsection, where it was shown that there is value in knowing the weather for both climate probability distributions, that not just precipitation but the variability in precipitation matters when making investment decisions. Even if a certain climate has a higher maximum precipitation value which in

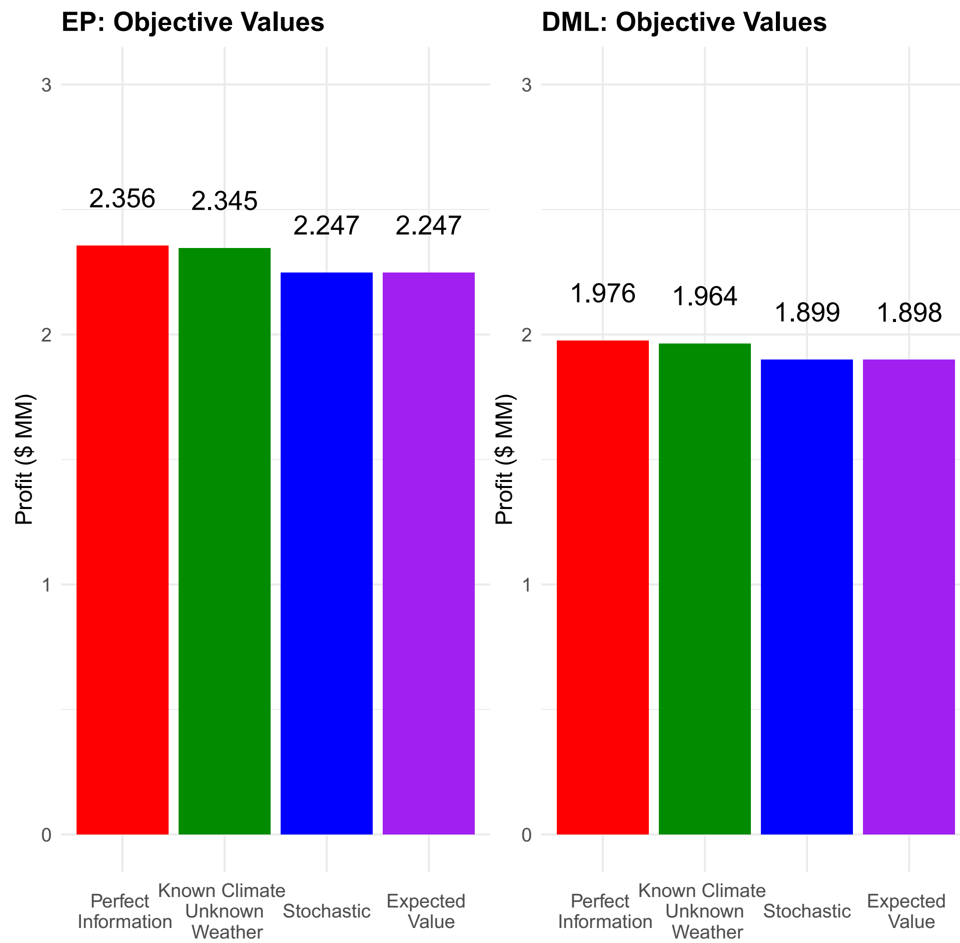


Fig. 1 The expected profits by climate probability distribution and solution

Table 4 The Expected Value of Perfect Information (EVPI), Value of the Stochastic Solution (VSS), Expected Value of Known Weather (EVKW), and Expected Value of Known Climate (EVKC) by climate probability distribution

Climate probability	EVPI	VSS	EVKW	EVKC
Equally probable	$108,725.10	$0.49	$10,396.32	$98,328.78
Dry most likely	$76,606.01	$940.90	$11,740.03	$64,865.98

turn raises the yearly average precipitation value, a tighter range and/or a higher median which reduces variability can reduce investment cost. More variability could lead to more investment that is underutilized in wetter years or insufficient capacity—that needs to be supplemented or in some cases that simply does not provide the optimal amount of water—in leaner years. This will be explored in the following subsections.

Table 5 Summary statistics for the profit and crop yield (CY) of all the solutions (Perfect Information [PI], Stochastic [Stoch], Expected Value [EV], Known Climate Unknown Weather [KCUW]) by Climate Probability (Equally Probable [EP] and Dry Most Likely [DML])

Solution	Profit mean	Profit std dev	Profit 95% CI ±	CY yearly means	CY std. dev.	CY 95% CI ±
EP-PI	2,355,663	635,133	19,691	2.866	0.909	0.00564
EP-KCUW	2,345,267	640,497	19,857	2.835	0.964	0.00598
EP-Stoch	2,246,938	616,454	19,112	2.674	1.114	0.00690
EP-EV	2,246,937	616,518	19,114	2.674	1.114	0.00690
DML-PI	1,975,827	490,655	15,212	2.771	0.840	0.00521
DML-KCUW	1,964,087	489,987	15,191	2.757	0.866	0.00537
DML-Stoch	1,899,221	424,374	13,157	2.666	0.929	0.00576
DML-EV	1,898,280	408,033	12,650	2.713	0.895	0.00555

4.2.2 Profit comparisons

Figure 2 shows the profits in the Stochastic solution for each climate, which all make the same investment decisions for a given climate probability distribution, all have profits less than or equal to their corresponding Known Climate Unknown Weather solution, which make different investment decisions depending on the climates.

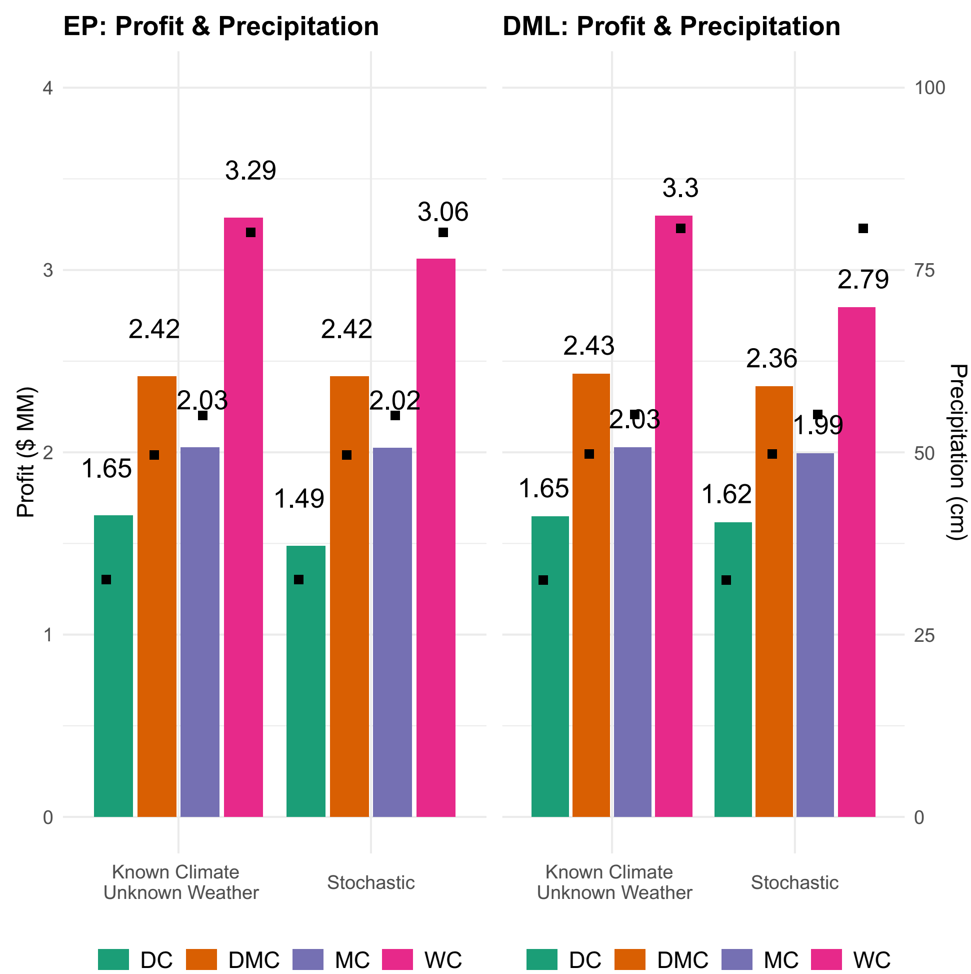
Figure 2 shows that there can be a significant difference between the Stochastic solution for a given climate and its corresponding Known Climate Unknown Weather solution. Nonetheless, if the Stochastic solution's investment decisions are close to its corresponding Known Climate Unknown Weather solution's decisions, the profit gap will be minimal. However, if the investment decisions are significantly different, this can lead to significantly lower profits. In the Dry Most Likely scenarios, that are shown in Fig. 2, the investor heavily weighs the probability of a Dry Climate. So, the difference between the Known Climate Unknown Weather and Stochastic Dry Climate solutions are minimal, but the differences between the Known Climate Unknown Weather and Stochastic profits for all other climates are significant. In other words, if the climate does not end up being Dry, the investment decisions made would be poorly aligned with any other climate realizations and come with significant costs. This will be explored in the following subsections.

4.3 Wheat yield comparisons: stochastic vs. known climate unknown weather solutions

Figure 3 shows that average annual wheat yields—illustrated with the bars and bar labels that correspond with the left y axis—do correlate with average total profit more so than average yearly precipitation. In this figure, we tracked average annual water depth, using the black triangles, instead of precipitation on the right y axis. This shows that increased average annual water depth does not necessarily lead to a proportional increase in crop yield. In the Known Climate Unknown Weather solutions the average yearly water depth for the Dry, Dry-Moderate, and Moderate climates are roughly the same but their wheat yields differ significantly.

These results suggest that there are a variety of factors that affect wheat yield. The most obvious factor is that the

Fig. 2 Average total profit and average yearly precipitation: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution



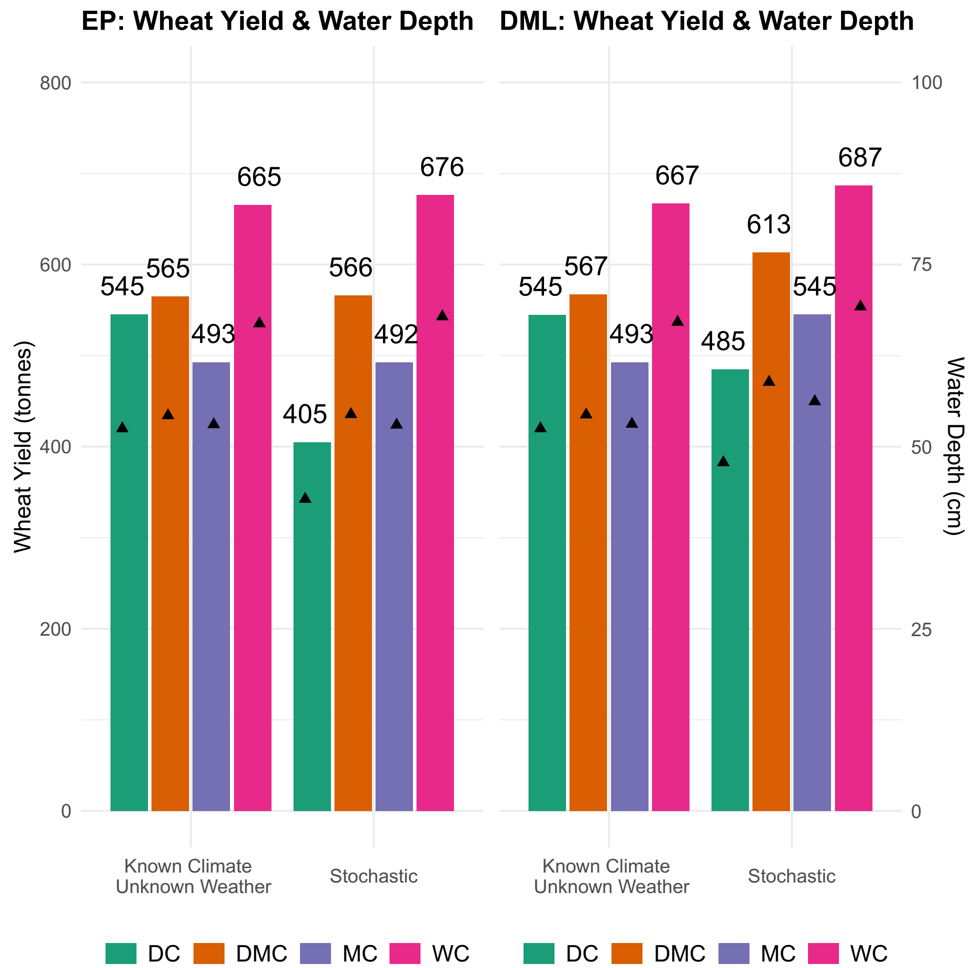


Fig. 3 Average annual wheat yields and water depth: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

wheat yield function is a quadratic production function where overwatering actually decreases yield. Furthermore, like for profit, the variability in weather and precipitation values can cause some years to have a high yield, while others have a significantly lower yield. And finally, the Dry solutions are able to better tailor their optimal water use because most years the amount of water they receive via precipitation is below their optimal water level and they can use alternative water technologies to reach but not exceed those optimal water levels. These factors will be explored in the following subsections.

4.4 Reverse osmosis capacity and solar PV investment decisions: stochastic vs. known climate unknown weather solutions

In this subsection, we investigate how reverse osmosis capacity and solar PV capacity investment decisions differ across solutions. We look into why a given solution invests in a specific amount of reverse osmosis capacity and/or solar PV capacity and investigate potential causes for the variations including average yearly precipitation values and yearly weather variability.

Figures 4 and 5 show that the Dry climate Known Climate Unknown Weather solutions invest the most in reverse osmosis capacity and solar PV capacity to make up for their shortcomings in precipitation. On the other hand, the Wet climate Known Climate Unknown Weather solutions do not invest at all in either because of their surplus of precipitation. Nonetheless, the moderate climates do not show a correlation between more precipitation and more investment.

This further highlights how weather variability among climates—more so than the average precipitation—drives investment decisions and can create inefficiencies in investments that drive up costs. The Moderate climate solutions invest in more reverse osmosis capacity than the Dry-Moderate climate scenarios because the model wants to ensure access to water in the dryer years. However, it invests in less solar PV capacity than the Dry-Moderate climate solutions because most years it does not need as much reverse osmosis capacity and by extension solar PV capacity due to higher rainfall in certain years and in the dryer years it can use utility electricity to meet any

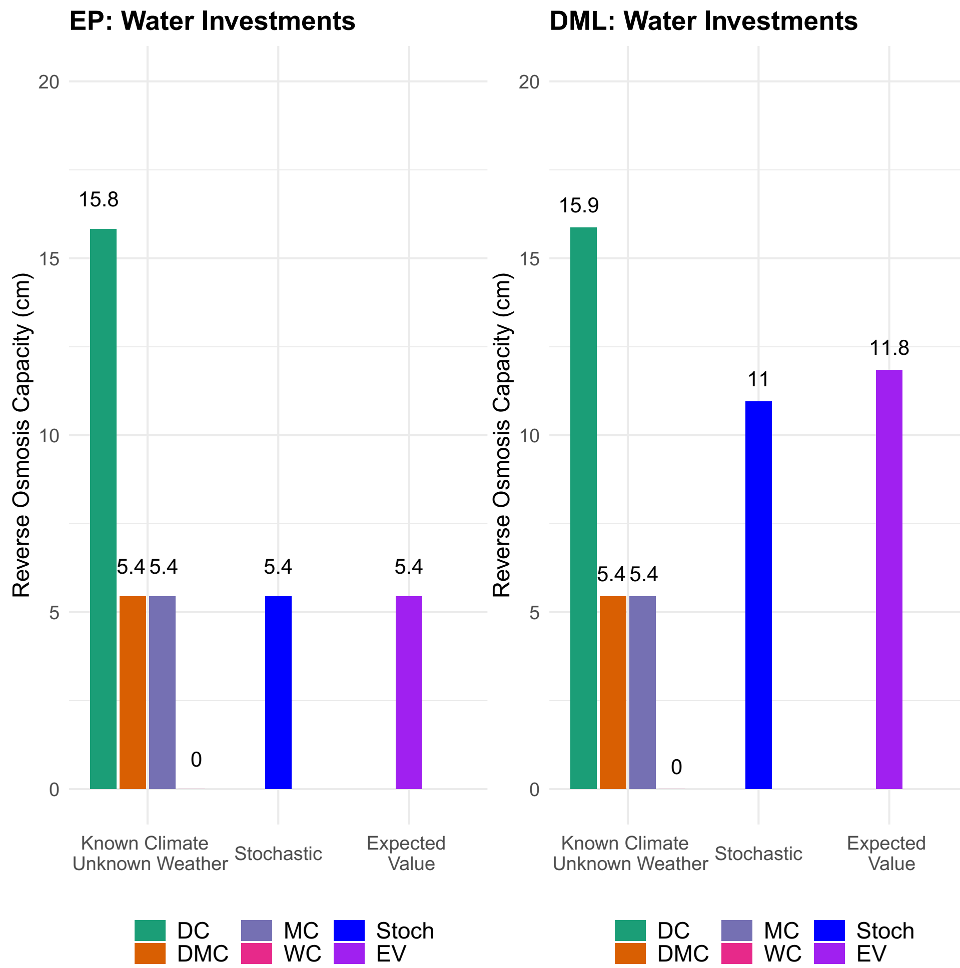


Fig. 4 Reverse osmosis capacity investment decisions: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

additional electricity demand. These conflicting investment decisions drive year-to-year inefficiencies that affect profit.

While the Known Climate Unknown Weather solutions are able to make different investment decisions based on the climate, the Stochastic and Expected Value solutions are only able to make a single set of investment decisions for all possible climate and weather realizations. Furthermore, the Stochastic solution makes an optimal decision by optimally hedging against all possible weather outcomes (which is simulated by 4000 possible weather outcomes), but the Expected Value scenario only optimizes its decision based on a single expected value weather realization. For the Dry Most Likely Expected Value solution this leads to a slightly different decision than the corresponding Stochastic solution which results in a small Value of the Stochastic Solution as shown in Table 4, but for the Equally Probable climate probability distribution the Expected Value and Stochastic solution investment decisions and by extension expected profits are virtually identical.

4.5 Water operations: stochastic vs. known climate unknown weather solutions

In this subsection, we investigate how the reverse osmosis capacity investment decisions affect water operations across scenarios. We look into why a given scenario invests in a specific amount of reverse osmosis capacity, how that affects operations, and investigate potential causes for the variations, including relationships between alternative water and groundwater use.

Figure 6 shows that the relatively moderate investment in reverse osmosis capacity by the Equally Probable Stochastic solutions results in less water capacity than is optimal for the Dry climate solutions, even with increased groundwater use. This results in less water being available for the crops and a subsequent reduction in crop yield and profit compared to the Known Climate Unknown Weather solution as shown in Figs. 2 and 3. However, for the Dry-Moderate and Moderate climates, the investment and as a result the operations are nearly identical.

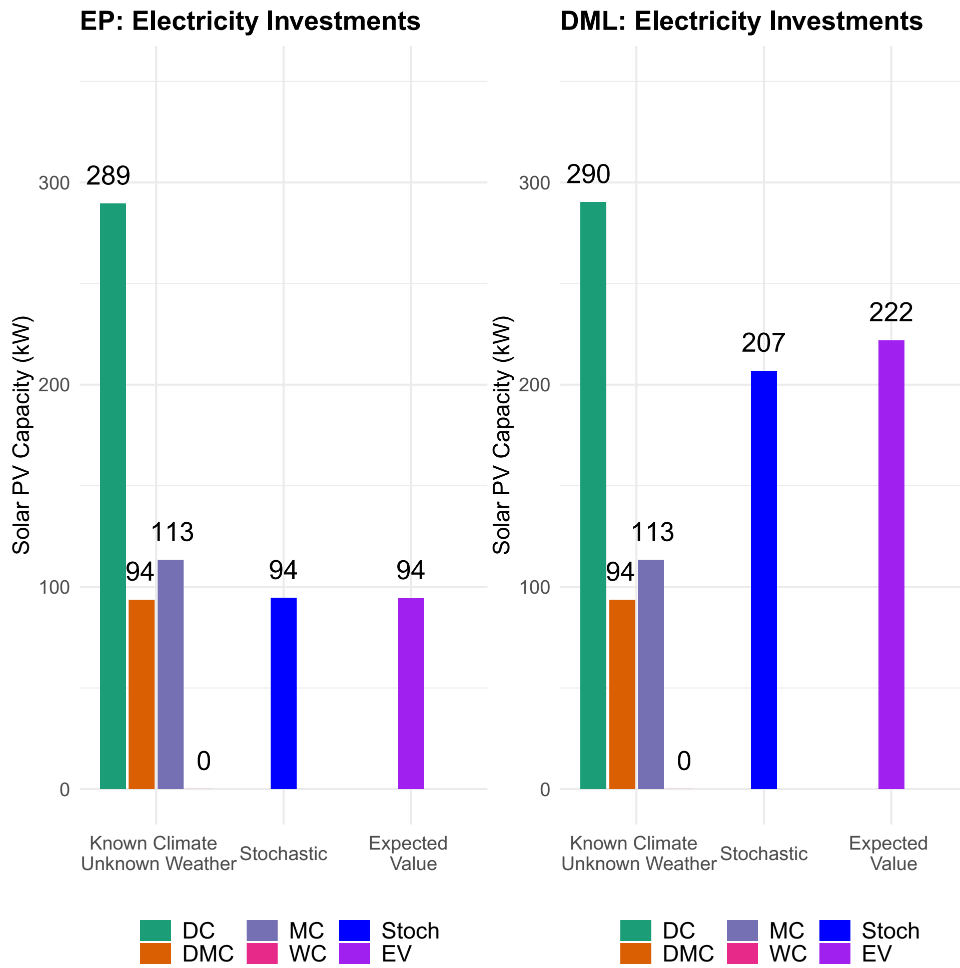


Fig. 5 Solar PV capacity investment decisions: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

On the other hand, Fig. 6 shows the large investments in reverse osmosis capacity by the Dry Most Likely Stochastic solution results in more reverse osmosis capacity than is optimal for all the climates, save the Dry climate. This results in an oversupply of relatively expensive reverse osmosis capacity. The increasing usage of reverse osmosis water even though it leads to an increase in crop yield as shown in Fig. 3 leads to a decrease in profit because of the extra expense as shown in Fig. 2.

4.6 Electricity operations

In this subsection, we investigate how the solar PV capacity investment decisions affect electricity operations across scenarios. We look into why a given scenario invests in a specific amount of solar PV capacity, how that affects operations, and investigate potential causes for the variations including variations in water use.

In general, solar PV capacity investments match reverse osmosis capacity investments and solar PV electricity use matches reverse osmosis water use. However, there are solutions where the investments in solar PV do not align with the optimal amounts of solar PV electricity. Figure 7 clearly illustrates that the solar PV electricity used in the Dry climate Equally Probable Stochastic solution is much less than in the corresponding Known Climate Unknown Weather solution. However, rather than increase its utility electricity use to fill in any gaps, it simply uses less water than what is optimal. The decrease in water used—because of the groundwater limits and the reduced investment in reverse osmosis capacity—is the most significant factor in the reduction of electricity use. This implies that reverse osmosis water use is the main driver for electricity use.

This is further emphasized in Fig. 7 where excess electricity does not lead to higher water usage in the Dry Most Likely solutions. While the investments in solar PV capacity do crowd out utility electricity, they do not encourage greater use of reverse osmosis water. This further supports the implication that reverse osmosis water use drives solar PV capacity investment.

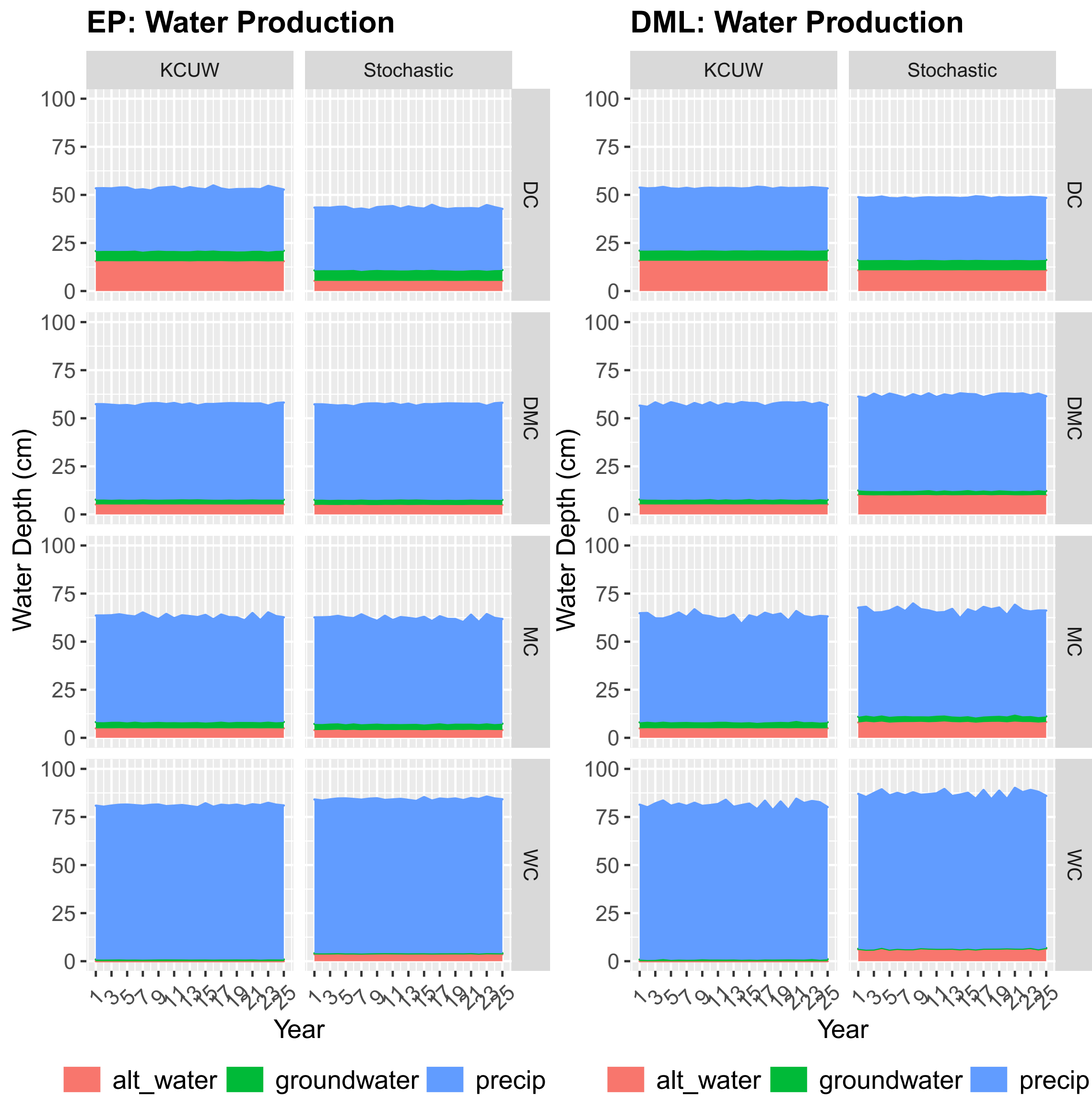


Fig. 6 Annual water operations: : Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

4.7 Summary statistics: stochastic vs. known climate unknown weather solutions

The profit and wheat crop yields reported in Figs. 2 and 3 are average values and as such represent a range of values. In order for these mean values to have significance, we calculated the 95% confidence intervals to ensure that our calculated mean values were indeed close to the true mean. The confidence intervals for profit and crop yield for all scenarios are extremely tight (less than ± \$0.03 MM for profit and less than ± 0.027 tons for crop yield) and show that the calculated means are very close to the true mean.

The standard deviations, on the other hand, encompass a much wider range of values and depend on the climate and climate probability distribution. A climate with a skew to certain weather realizations, like the Wet and Dry climates, has a smaller standard deviation than the Moderate climate where all weather realizations are equally likely. This reinforces the reasoning that variation in weather realizations heavily influences profit even more than average precipitation.

Note, while the Equally Probable solutions' climates all had 1000 samples, the Dry Most Likely scenarios' climates' samples ranged from 200 samples to 2400 samples, which affects both the standard deviation and confidence intervals. However, this does not result in major differences and all the general trends mentioned above still hold. All the means, standard deviations, and 95% confidence interval statistics are shown in Tables 6 and 7.

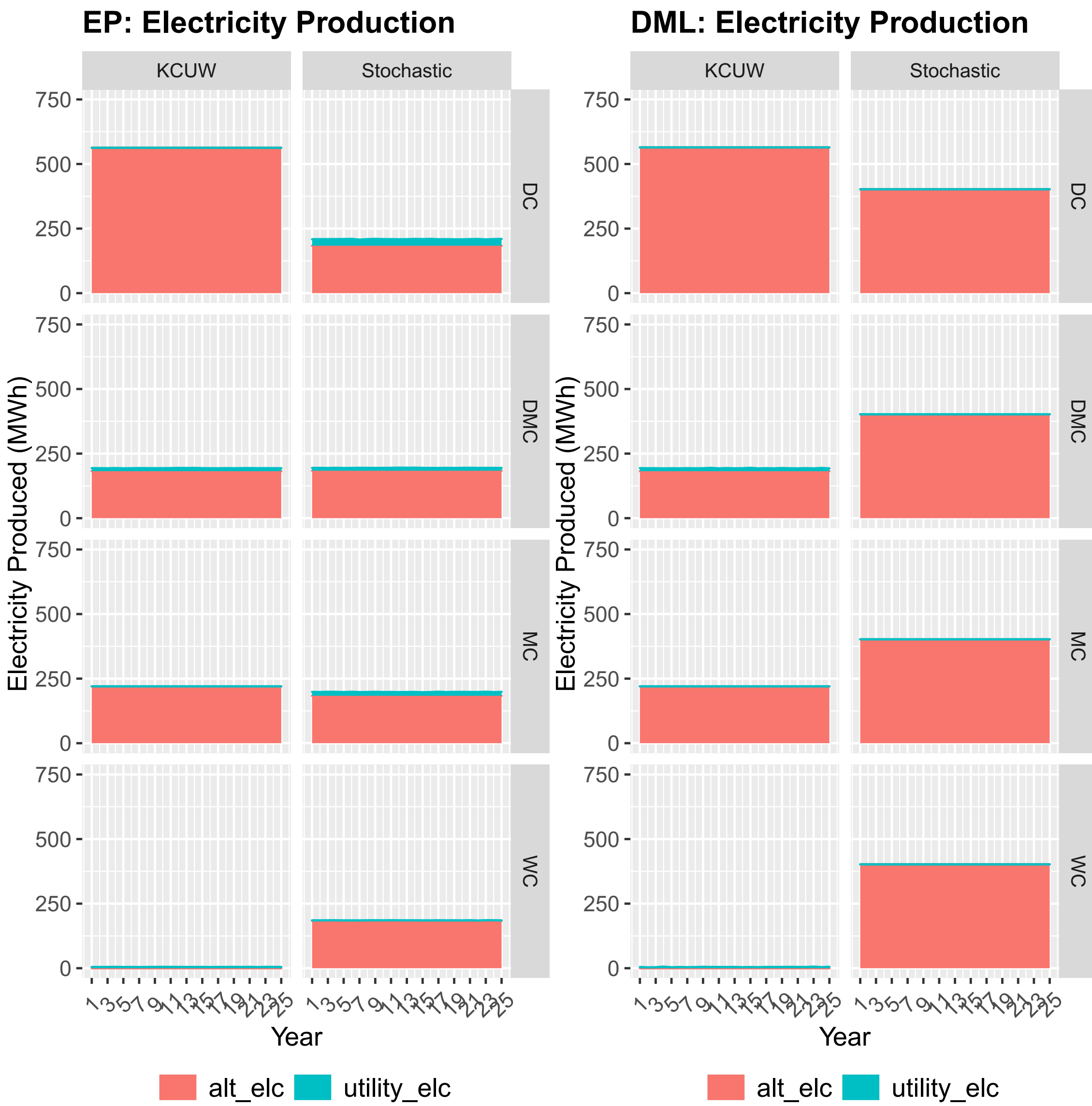


Fig. 7 Annual electricity operations: : Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

Table 6 Equally Probable climate probability distribution: summary statistics for the profit and crop yield (CY) of the Stochastic (Stoch) and Known Climate Unknown Weather (KCUW) solutions by climate (Dry [DC], Dry-Moderate [DMC], Moderate [MC], Wet [WC])

EP scenario	Profit mean	Profit std dev	Profit 95% CI ±	CY yearly means	CY std. dev.	CY 95% CI ±
DC-KCUW	1,652,488	170,907	10,611	2.726	0.762	0.00944
DC-Stoch	1,486,498	253,577	15,744	2.024	1.146	0.01421
DMC-KCUW	2,416,584	206,384	12,813	2.824	0.865	0.01072
DMC-Stoch	2,416,521	206,139	12,798	2.830	0.867	0.01075
MC-KCUW	2,025,712	291,547	18,101	2.464	1.344	0.01667
MC-Stoch	2,024,500	297,946	18,498	2.462	1.343	0.01665
WC-KCUW	3,286,282	106,040	6,584	3.327	0.439	0.00544
WC-Stoch	3,060,232	79,790	4,954	3.381	0.318	0.00394

Table 7 Dry Most Likely climate probability distribution: summary statistics for the profit and crop yield (CY) of the Stochastic (Stoch) and Known Climate Unknown Weather (KCUW) solutions by climate (Dry [DC], Dry-Moderate [DMC], Moderate [MC], Wet [WC])

DML Scenario	Profit Mean	Profit Std Dev	Profit 95% CI ±	CY Yearly Means	CY Std. Dev.	CY 95% CI ±
DC-KCUW	1,648,352	170,789	6,838	2.724	0.765	0.00612
DC-Stoch	1,616,243	206,780	8,279	2.425	0.941	0.00753
DMC-KCUW	2,430,358	196,029	12,171	2.836	0.847	0.01050
DMC-Stoch	2,361,189	153,639	9,539	3.066	0.664	0.00824
MC-KCUW	2,026,811	301,300	29,654	2.464	1.354	0.02654
MC-Stoch	1,994,689	244,732	24,086	2.725	1.074	0.02106
WC-KCUW	3,296,111	110,519	15,449	3.335	0.427	0.01184
WC-Stoch	2,794,189	59,309	8,291	3.434	0.209	0.00581

5 Conclusions

In this model, there are two main uncertainties that the farm decision maker must consider: the future climate and the year-to-year precipitation amounts within that climate. These uncertainties affect a decision maker's investment decisions which in turn affect the operations of the farm, followed by the crop yield and finally the profit.

The climate uncertainty is the biggest factor affecting profit as illustrated by the relatively large difference between the Stochastic and Known Climate Unknown Weather solutions, but the much smaller difference between the expected value of the Known Climate Unknown Weather and Perfect Information solutions. More conservative investment decisions can balance this downside risk and even increase the upside if more moderate climates are realized, as shown in the Equally Probable solutions. However, if the climate will actually be at one of the extremes, then more aggressively hedging toward that climate will provide a higher profit than a more conservative investment as shown by the Dry Most Likely solutions.

Nonetheless, optimally hedging seems to provide limited benefit compared to simply preparing for the average possible climate. The Stochastic solution's investment decisions and the Expected Value solution's investment decisions are nearly identical for the Equally Probable climate probability distribution. For the Dry Most Likely climate probability distribution, there is only a slight difference between the Stochastic and Expected Value solutions' investment decisions. Nonetheless, this reflects that the defined climate probability distributions are relatively moderate where the average climate and by extension precipitation values are close to the given Moderate and Dry-Moderate climates. Climate probability distributions where the average never occurs, like a 50% chance of a Wet Climate and a 50% chance of a Dry Climate, would likely increase the Value of the Stochastic Solution.

While climate uncertainty is the biggest factor affecting profit, the year-to-year weather variability for a given climate can also cause significant swings in crop yield and, therefore, profit. In fact, the differences in profit between the Perfect Information solutions, where the climate and the weather are known, and the Known Climate Unknown Weather solutions, where the climate is known but the weather is uncertain, are larger than the Values of the Stochastic solutions.

The swings in precipitation from year to year can corrode overall profits by having a reverse osmosis capacity and/or solar PV capacity investment be undersized one year and oversized another. The extra costs incurred because of the mismatch between invested capacity and the year-to-year optimal capacities—even when the invested capacity matches the yearly average optimal capacity—add up. This explains why the Moderate climate scenarios are less profitable than the Dry-Moderate climate scenarios, even though the Moderate climate has a higher average yearly precipitation value.

While both of these uncertainties are outside of the farmer's control, especially with regard to the weather variations for a given climate, understanding how a decision maker's investments and by extension their profits could be affected by these uncertainties is important. For instance, a more risk-taking operator might be more willing to heavily weigh a specific climate to maximize upside than a more risk-averse operator. This model allows an operator to examine how climate probability distributions affect profit for a variety of climate realizations not just based on what he believes the climate will be, but on a representative sample of climate possibilities in order to provide the operator with a fuller picture on how investment decisions in the present could affect profits in the future.

5.1 Limitations

This model provides a general framework for farm investment and operational decisions, but does not answer detailed questions about water schedules or even solar production. It abstracts many of the day-to-day operational decisions in exchange for a big picture year-by-year framework which could significantly affect profit and yield. Other works in this area of research have done the opposite and have added more detailed information and have added more sectors like energy, climate, and water treatment to the basic crop yield model to provide even more accurate insights. We believe our simpler model allows for more insights on a larger variety of scenarios; however, we concede that it sacrifices accuracy. Future works could add more day-to-day or sector-specific detail to allow for more accurate insights while balancing the ability for our framework to investigate a large number of scenarios quickly.

5.2 Future directions

This model, in the most general sense, is a stochastic framework to help a decision maker deal with climate risk and resource uncertainty. In this study, we investigated how climate uncertainty and water scarcity would affect a farm decision maker's investment and operational decisions to deal with those problems. However, any sector that has to deal with climate uncertainty and resource constraints could benefit from this framework. In the future, this modeling framework could be used to investigate heating and cooling demand and the generation resources needed to meet it, urban food and water demand, energy generation investment decisions, and optimal electricity distribution networks.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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