Quantifying the Value of Learning for Flexible Water Infrastructure Planning

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Key Points:

- We present a framework to assess how the rate of learning about climate uncertainty affects the value of flexible water infrastructure
- Exploratory Bayesian modeling generates climate learning scenarios with high and low potential to reduce future precipitation uncertainty
- In a case study in Mombasa, Kenya, flexible water infrastructure is valuable in high-learning scenarios and wet precipitation conditions

Abstract

Uncertainty in future climate change challenges water infrastructure development decisions. Flexible infrastructure development, in which infrastructure is proactively designed to be changed in the future, can reduce the risk of overbuilding unnecessary infrastructure while maintaining reliable water supply. Flexible strategies assume that water planners will learn over time, updating future climate projections and using that new information to change plans. Previous work has developed methods to incorporate learning using climate observations into flexible planning but has not quantified the impact of different amounts of learning on the effectiveness of flexible planning. In this work, we develop a framework to assess how differences in the amount of learning about climate uncertainty affect the value of flexible water infrastructure planning. In the first part of our framework, we design climate scenarios with different amounts of learning using an exploratory Bayesian modeling approach. Then, we quantify the impacts of learning on flexibility using simulated costs and infrastructure decisions. We demonstrate this framework on a stylized case study of the Mwache Dam near Mombasa, Kenya. Flexible planning is more effective in avoiding over- or underbuilding under high-learning scenarios, especially in avoiding overbuilding in wet climates. This framework provides insight on the climate conditions and learning scenarios that make flexible infrastructure most valuable.

1 Introduction

Climate change uncertainty challenges water supply planning (Gleick, 1989, 2000). Infrastructure systems, which are designed to last for many decades, must perform well under highly uncertain conditions (Cosgrove & Loucks, 2015; IPCC, 2022). Traditional water supply planning approaches usually oversize water infrastructure using a safety factor to account for uncertainty and reduce the chance of system failure (Stakhiv, 2011). However, overbuilding adds costs and environmental impacts, which are especially detrimental in more resource-scarce regions. One strategy to plan under uncertainty is flexible planning. Flexible, or adaptive, planning approaches can help mitigate infrastructure over- or underbuilding by changing the design or operations of infrastructure to respond to evolving conditions over time (Bertoni et al., 2021; Culley et al., 2016; Hui et al., 2018). For example, flexible plans may respond to hydrologic shifts, like a climate trending drier (Kumar et al., 2013), or changing societal values, such as a focus towards sustainability and ecological benefits (Kermisch & Taebi, 2017). Flexible plans also have downsides. They require identifying signs of system vulnerability (Dewar et al., 1994; Haasnoot et al., 2013) to trigger adaptations (Walker et al., 2001), which assumes that we can identify a reliable signpost for when to adapt. This may not be the case in many systems (Raso et al., 2019). Flexible plans also are expensive and may require additional costs for monitoring systems or repetitive structural elements to allow for future adaptations (Moore & McCarthy, 2010; Spiller et al., 2015; Walters, 1997).

How much we can learn about uncertainty in the future informs whether a flexible approach is favorable. To take a flexible approach, we must have an iterative process where new information becomes available, the system processes that information, and then changes accordingly (Pahl-Wostl, 2007). In this context, the value of learning depends on how much new information improves decision making (Williams, 2011). We categorize learning mechanisms, or types of information integration, through which we can learn. One mechanism is *learning by model improvement*, where epistemic uncertainty is improved through the development of better models (Walters, 1997; Williams & Brown, 2016). This type of learning reduces uncertainty through the improved understanding of physical and socioeconomic processes. Another mechanism is *learning by active information incorporation*, by seeking out and including additional sources of information. Examples include developing and incorporating short- and long-term precipitation forecasts (Zaniolo et al., 2021) and developing new groundwater monitoring systems (Storck et al., 1997). A last mechanism is *learning by observation*, in which monitoring of relevant system variables, such as climate trends, are used to update future projections (Conroy et al., 2011; Ekholm, 2018; Giuliani et al., 2019; Pulwarty & Melis, 2001). In learning by observation, the ability to learn is informed by how correlated near-term observations are with long-term trends. For example, if near-term and long-term trends are highly correlated, observing an upward trend in a climate variable in recent years indicates a long-term upward trend in the future. In this case, ongoing climate observations reduce future climate uncertainty, and the climate has a high learning rate. Conversely, when the correlation is low, a recent trend does not indicate a future long-term trend, future climate uncertainty remains unchanged, and learning does not occur, or occurs slowly.

Within water supply planning models focused on climate change uncertainty, most planning approaches do not account for learning about uncertainty. Global climate models (or general circulation models; GCMs) provide the best available projections for future climate conditions. Planning models often use ensembles of different GCMs to simulate system performance under uncertainty and identify approaches that perform well across plausible future scenarios (Brown & Wilby, 2012; Lamontagne et al., 2018; Quinn et al., 2020; Steinschneider et al., 2015). This approach uses a static representation of uncertainty, in which the range of plausible futures identified at the outset remain plausible throughout the planning period. However, it may be possible to refine the likelihood of future projections as new observations become available (Abramowitz & Bishop, 2015; Massoud et al., 2020; Sanderson et al., 2017; Urban et al., 2014; Urban & Keller, 2010). Bayesian Model Averaging (BMA) has been used to determine the influence of multiple climate models on future aggregated projections based on observational data (Duan & Phillips, 2010; Gibson et al., 2019; Massoud et al., 2020). BMA develops a set of updated climate projections by averaging prior estimates from the different climate models based on how well each model captures historical observations.

In the water resources literature, closed loop planning approaches have been used to explicitly incorporate learning to inform decision making over time. Closed loop planning approaches include multiple classes of methods, including policy search and dynamic programming (Herman et al., 2020). Policy search approaches use simulation-based optimization to find a decision policy that minimizes a given objective function (see, e.g., Giuliani et al., 2016). Policy search has been paired with learning by active information incorporation through the addition of exogenous information to condition policy decisions. More informed policies generally result in improved policy outcomes (e.g., Giuliani et al. 2019; Woodward, Kapelan, and Gouldby 2014). Policy search methods have been used in flood (Ceres et al., 2022; Kwakkel et al., 2015, 2016; Woodward et al., 2014) and urban water supply (Mortazavi-Naeini et al., 2015; Paton et al., 2014; Zeff et al., 2016) infrastructure planning.

One benefit of dynamic programming is that new information can be explicitly incorporated at each time step using a prescribed probability distribution, and the problem formulation incorporates all potential future information in determining the optimal planning decisions (Fletcher, Lickley, et al., 2019; Giuliani et al., 2016). Dynamic programming and optimization methods with Bayesian updating frameworks have been used in flood (Doss-Gollin & Keller, 2022; Hui et al., 2018) and flexible water (Fletcher, Lickley, et al., 2019) infrastructure planning problems. Jeuland & Whittington (2014) use decision trees, which use dynamic programming as solution method but do not make the Markov assumption typical in larger problems, within an engineering options analysis simulation framework to systematically evaluate infrastructure selection, sizing, and sequencing. Fletcher, Lickley, and Strzepek (2019) develop the first planning framework to explicitly incorporate learning about climate change uncertainty into the upfront flexible infrastructure planning decision. They use Bayesian modeling (Smith et al., 2009) to develop future temperature and precipitation uncertainty projections and use learning by observation of the climate state to compare flexible and static infrastructure planning approaches. However, this work did not test how different climate learning rates impact costs and planning decisions to understand the conditions under which flexible water infrastructure is most valuable.

This gap is the motivation for our current work. We develop a framework to assess how differences in the amount of learning about climate uncertainty affect the value of flexible water infrastructure in providing low-cost, reliable water supply. One key contribution is the use of information theory metrics to quantify uncertainty changes. We demonstrate this framework on a stylized dam planning case study. To assess the effect of variable learning rates, we design future climate scenarios with different rates of learning by observation using an exploratory Bayesian modeling approach. Then, we develop an approach to quantify the impacts of learning about climate change uncertainty on flexible and static infrastructure designs. We demonstrate this framework on the Mwache Dam near Mombasa, Kenya. GCMs in this region have diverging future precipitation projections with long-term uncertainty on whether this area will become wetter or drier. We find that a high-learning climate often increases the value of flexibility and better avoids over- or underbuilding infrastructure compared to a low-learning climate. We also find that flexible infrastructure is most valuable under wet climate conditions by avoiding overbuilding.

2 Methods

2.1 Case study: Mwache Dam in Mombasa, Kenya

We apply our framework to the Mwache Dam near Mombasa, Kenya. The Mwache Dam site, Mwache River, and associated tributaries are shown in Figure 1a. The dam is about 22 kilometers west of Mombasa, Kenya. The dam's main purposes are to meet water supply for growing urban and agricultural demands in the region. Over the next 15 to 20 years, urban water demands are expected to double in Mombasa (Ojwang et al., 2017). Additionally, as part of the infrastructure project, planned irrigation districts will receive water from the dam (State Department of Natural Water Services, 2016), as highlighted on the map.

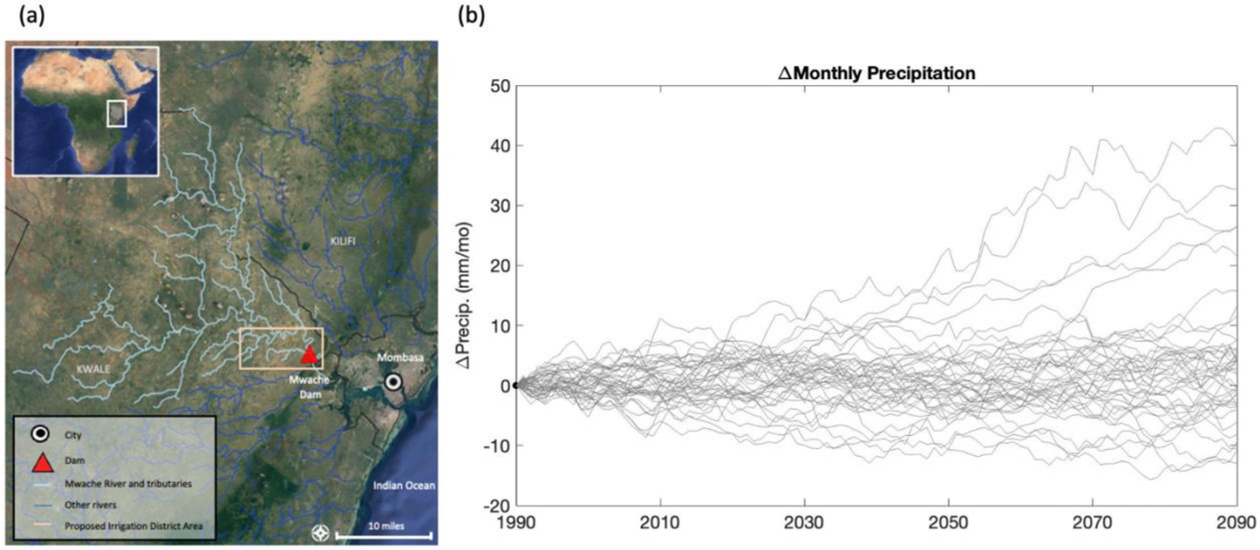

Figure 1. Case study location. a) Map of Mwache River and tributaries, b) RCP4.5 and RCP8.5 GCM projections for 20-year precipitation moving averages near Mombasa, Kenya.

Figure 1b shows the projected precipitation change in Mombasa relative to a 1990 baseline under 21 GCMs for RCP4.5 and RCP8.5 emissions pathways. Table S1 in the Supplementary Information (SI) includes the full GCM list. The diverging trend for different GCMs highlights the large uncertainty in future precipitation trends in this region due to climate change. This diverging trend challenges water supply planning and motivates the use of flexible water infrastructure to avoid over- or underbuilding.

2.2 Framework Overview

We develop a novel framework to assess how different rates of learning about precipitation affect the value of flexible infrastructure in low-cost, reliable water supply. Our approach has three key steps, illustrated in Figure 2. First, in panel a, we develop two contrasting climate learning scenarios: a high-learning climate scenario where new observations are correlated with past observations and substantially reduce future uncertainty, and a low-learning climate scenario where new observations are uncorrelated and therefore less informative. In parallel, we design two infrastructure alternatives: a static dam that cannot be modified once built, and a flexible dam that can be expanded at most once during the planning period. Second, we develop an infrastructure planning model using stochastic dynamic programming (SDP) (hereafter termed infrastructure planning SDP) to evaluate the infrastructure and shortage costs of the optimized static and flexible dam alternatives in the high- and low-learning climate scenarios. We use a 100-year time horizon with new climate information incorporated and actions updated every 20 years. Finally, in panel b, we use these results to quantify the value of flexibility, defined as the cost savings of the flexible dam compared to the static dam. We then quantify the value of learning for flexibility, defined as the difference in the value of flexibility in the high-learning climate compared to the low-learning climate. This framework allows us to assess the interaction between learning about climate uncertainty and infrastructure flexibility, and to quantify the degree to which greater learning improves the value of flexible planning.

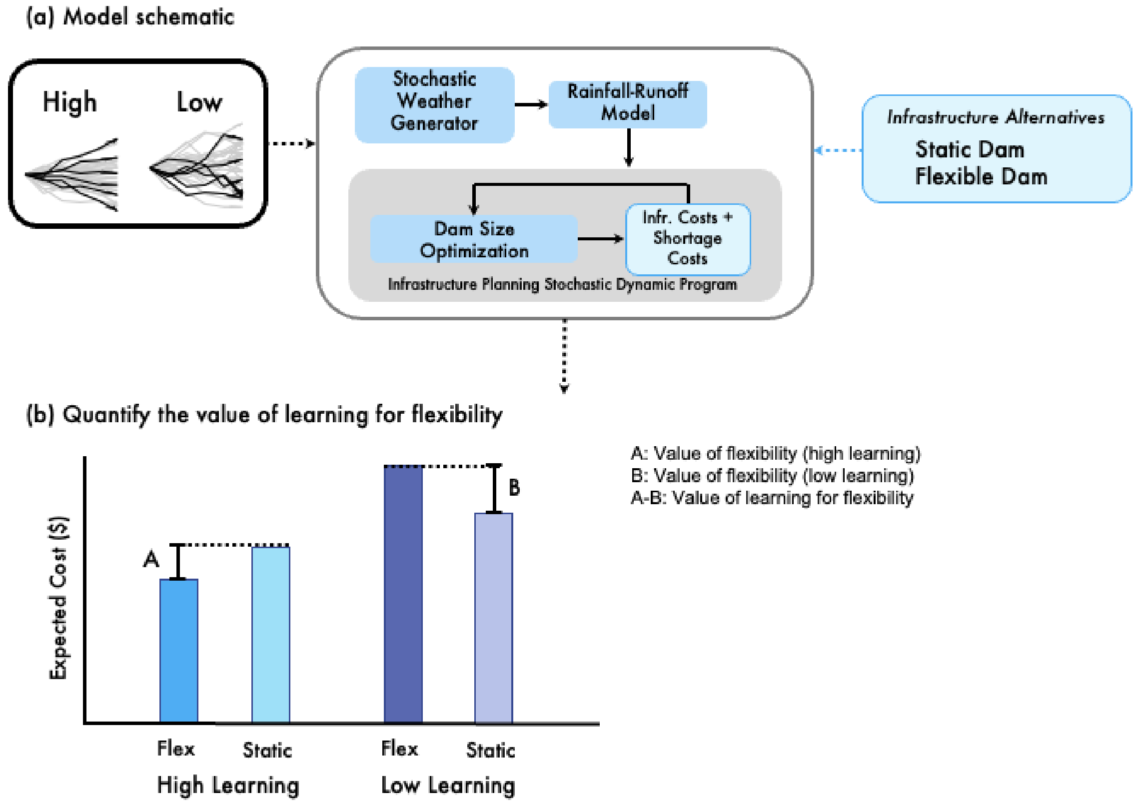

Figure 2. Schematic illustrating framework for quantifying the value of learning about climate uncertainty for flexible water infrastructure

2.3 Designing Climate Learning Scenarios

First, we develop climate learning scenarios that model learning by observation using exploratory Bayesian updating, in which we systematically adjust the likelihood function to change the influence of new observations on the posterior. In our exploratory Bayesian model, the prior distribution reflects the full range of uncertainty in future precipitation projections at the outset of the planning period. As the planning period goes on, more data about how precipitation is changing becomes available, which is used to update the prior and develop a posterior distribution. The difference between the posterior and prior distributions reflects what is learned about uncertainty from the new data. Here the new data is synthetic data that corresponds to simulated precipitation in the infrastructure planning model.

We design two scenarios, a high-learning climate and a low-learning climate. In the high-learning climate scenario, new observations have a large influence on the prior, leading to a posterior that substantially narrows around the new data. In the low-learning climate scenario, new observations have a limited effect, and the posterior more closely resembles the prior, reflecting slow learning. In Bayes' theorem, the likelihood function controls the degree to which the posterior is changed by new data. Therefore, we design the high- and low-learning climate scenarios by developing likelihood functions with low and high variance, respectively. In previous work that integrates climate model projections with observational data (e.g. Smith et al.

2009), the likelihood function describes the error between observed and modeled projections of precipitation change. Models with larger historical errors have likelihood functions with higher variance terms, leading to less influence on the posterior. Here, as an exploratory approach to vary the amount of learning, we directly manipulate the variance of the likelihood function to control the amount of influence the new synthetic observation has on the posterior.

Our Bayesian model is presented in Equation 1. We model a single period update, where precipitation change in time t is used to update the projection for precipitation in t+1. This choice is made to align with the formulation of our stochastic infrastructure planning model, which uses single-period Markov state transitions. We develop projections to the end of the planning period by applying Monte Carlo simulation to the single period transitions. We use a normal-normal conjugate model for the single period update. The assumption of normality aligns with previous work modeling precipitation change (Ruosteenoja et al., 2007) and is validated using a Kolmogorov-Smirnov (K-S) test. The K-S test results are listed in SI Section S2.

In t=1, the model is:

$$P(\Delta p_1) \sim N(\Delta p_0, \sigma_0^2) \qquad \text{(Prior in t=1)}$$

$$P(\Delta p_0 | \Delta p_1) \sim N(c_l \Delta p_0,\ \alpha_l) \qquad \text{(Likelihood in t=1)}$$

$$P(\Delta p_1 | \Delta \mathrm{p}_0) \sim N(\mu_1 \Delta p_0, \nu_1 \sigma_0^2) \qquad \text{(Posterior in t=1)}$$

$$\text{where } \mu_1 = \frac{\mathrm{c_l} * \sigma_0^2 + \alpha_l{}^2}{\sigma_0^2 + \alpha_l{}^2},\ \nu_1 = \frac{\alpha_l{}^2}{\sigma_0^2 + \alpha_l{}^2}$$

Equation 1

This model uses a recursive approach in which the posterior from one time period becomes the prior in the next; in the t=1 model, Δp_0 is the "synthetic observation" i.e. precipitation change in the previous (t=0) period that is used to update estimated precipitation change in the current (t=1) period.

Using the same single-period likelihood function, $P(\Delta p_{t-1} | \Delta p_t) \sim N(c_l \Delta p_{t-1},\ \alpha_l)$, we derive the general posterior for any time period:

$$P(\Delta p_t | \Delta \mathrm{p}_{t-1}, \dots, \Delta \mathrm{p}_0) \sim \mathrm{N}(\mu_t \Delta p_{t-1}, \nu_t \sigma_0^2)\ \forall t \geq 0$$

$$\text{where } \mu_t = \frac{t * \mathrm{c_l} \sigma_0^2 + \alpha_l{}^2}{t * \sigma_0^2 + \alpha_l{}^2},\ \nu_t = \frac{\alpha_l{}^2}{t * \sigma_0^2 + \alpha_l{}^2}$$

Equation 2

We define the terms in this model as follows. $\Delta \mathrm{p_t}$ is the change in precipitation ending in time t relative to the current time period, t=0. σ_0^2 is the variance of the prior in t=0, reflecting current knowledge of precipitation change uncertainty. We define the mean of the likelihood using a multiplicative shifting factor, c_l, which controls the lag-1 autocorrelation in Δp. The subscript l refers to the climate learning scenario, which can be high $(l = H)$ or low $(l = L)$. c_l is greater in the high-learning scenario than the low-learning scenario, representing the correlation between near-term observations and long-term change. α_l is the variance of the likelihood, where higher values are analogous to greater error between climate models and observations, leading to lower learning by observation. c_l and α_l are parameters we manipulate directly for exploratory analysis. Together, they control the amount of learning, with c_l determining how correlated near-term precipitation is with long-term precipitation, and α_l

determining how much the new observation affects the prior estimate. Finally, μ_t and ν_t are derived using the normal-normal conjugate (Marin & Robert, 2007).

The numerical values of these parameters are given in Table 1. σ_0^2 was chosen to be comparable to the variance of one-period changes in precipitation in the ensemble of GCM projections in Mombasa. c_l and α_l were chosen with two goals. First, we choose higher c_l and lower α_l in the high-learning scenario compared to the low-learning scenario, reflecting greater autocorrelation and greater updating based on new information, both of which lead to more learning. Second, we want the end-of-century prior precipitation distributions to be the same and comparable to the mean and variance across GCM projections. This ensures that the difference in the scenarios reflect differences in learning rather than differences in precipitation trends or initial uncertainty. The method used is discussed in SI Section S3.

Table 1. High- and Low-Learning Climate Scenario Parameters

Learning scenario	σ_0	c_l	α_l
High	5.0	1.15	2
Low	5.0	-0.58	50

2.4 Quantifying Learning

The previous section described our approach to designing scenarios that reflect high and low rates of learning by observation about climate uncertainty. Here, we quantify the amount of learning in each model simulation. This serves two purposes. First, it allows us to validate that the approach to design high- and low-learning climate scenarios does indeed lead to differences in learning. Second, it allows us to quantify the amount of learning across different model simulations, which we use to assess the impact of different amounts of learning on flexibility. We quantify the change in predicted precipitation distributions using KL divergence, an information theory metric that measures the amount of information gain through comparing two distributions (Kullback & Leibler, 1951). The KL divergence between the posterior and prior in a Bayesian model is commonly used to measure the amount of learning from new observations (Gelman et al., 2021). Previous climate science and water resources work uses KL divergence to compare synthetic climate projections, such as precipitation or streamflow, with observed data (e.g., Leung and North 1990; Nearing and Gupta 2015; Weijs, Schoups, and van de Giesen 2010).

Here we use KL divergence to quantify the amount of learning by observation in probabilistic precipitation change projections. We apply Monte Carlo simulation to our Bayesian model for single period transitions (Equations 1 and 2) to develop probabilistic precipitation change projections starting in our initial time period (1990; t=0) through the end of our modeled planning period (2090; t=5) with a time step of 20 years. We vary the number of recursive Bayesian updates corresponding to how many years of new precipitation observations are used for learning. We define our prior as the information available in 1990 (t=0). Then we can develop a posterior for any future time period t based on new observations between time 0 and t-1. For example, we can simulate precipitation distributions for the year 2090, using observations through the year 2070; this requires simulation through four Bayesian updates, each corresponding to a new 20-year average observation. In this example, we define 1990 as the prior year, 2070 as the information year, and 2090 as the projection year. Further, we propagate uncertainty through our simulation model using Monte Carlo simulation to develop analogous projections and updates for water shortages in addition to precipitation. We apply KL divergence to calculate learning between prior and posterior projections using a distribution of precipitation or water shortage predictions. For discrete distributions, this is calculated as shown in Equation 3:

$$D_{KL}\left(P_{t,i} \| P_{t,p}\right) = \sum_{x \in X} P_t(x) * \log \frac{P_{t,i}(x)}{P_{t,p}(x)},$$

Equation 3

where $P_{t,i}(x)$ is the probability distribution for precipitation (or water shortages) in projection year t based on observations between t=0 and information year i, and $P_{t,p}(x)$ is the probability distribution at projection year t, based only on information from prior year p. x is a discrete random variable representing possible values of future precipitation (or water shortages). A discrete formulation was chosen to align with the infrastructure planning SDP, which constrains precipitation (and water shortage) values to discretized increments; see below. We follow recommendations from Gong et al. (2014) for applying KL divergence to precipitation and water availability data. See SI Section S4 for details.

2.5 Infrastructure Planning Model using Stochastic Dynamic Programming

After developing the climate learning scenarios and an approach to quantify the learning in each, we now develop an infrastructure planning model that uses SDP to optimize and compare the performance of static and flexible infrastructure alternatives under the contrasting climate learning scenarios. The infrastructure planning SDP identifies the least-cost infrastructure planning policy under climate uncertainty over a 100-year time horizon with 20-year time steps. Climate uncertainty is incorporated into the infrastructure planning SDP by defining a state variable that represents average precipitation in each 20-year period. We use the Bayesian model from Equations 1 and 2 to characterize the transition probabilities for the precipitation state variable. The current precipitation state in the SDP is used as the synthetic data $\Delta \mathrm{p}_\mathrm{t}$ in the Bayesian model. The transition probabilities that lead to future precipitation states therefore reflect what is learned from the current state as an observation. This approach integrates learning by observation into optimal infrastructure planning policies. This approach was developed and applied in Fletcher, Lickley, and Strzepek (2019) and Fletcher et al. (2019). We formulate and solve the infrastructure SDP using the Bellman equation (Bellman, 1954) as follows:

$$V_t(s_t) = \underset{a \in A}{\operatorname{argmin}}\ C(s_t, a_t, t) + \gamma * \sum_{s \in S} P(s_{t+1} | s_t, a) * V_{t+1}(s_{t+1})$$

Equation 4

where $t \in \{1, \ldots, 5\}$ for 20-year planning periods from t=1 representing 2001-2020 to t=5 representing 2081-2100. S is the state space, comprising state variables S^P for the precipitation state, which ranges from 49 to 119 millimeters per month in discretized one-millimeter bins, and

S^Z for the infrastructure state, which comprises the static dam, flexible dam unexpanded, or flexible dam expanded to multiple candidate sizes. A is the set of actions: what dam to construct in the first time period, and if and how much to expand the flexible dam in later time periods. C is the cost function comprising capital costs and water shortage costs, and V is the value function, the lowest cost in each state and time. γ is the discount rate; we include scenarios for 0% and 3%. A 3% discount rate is commonly used in climate change analysis work on infrastructure development in Africa (Cervigni et al., 2015). Zero discounting was chosen as a contrasting example where there is no preference for the present over the future. This allows us to isolate the value of flexibility in addressing uncertainty from the value of flexibility driven by discounting, which incentivizes the delay of capital costs. P is the transition probability of transitioning to a given future state s_{t+1} in the next time period based on the current state s_t and our action a. The transition probabilities for state vectors S^P and S^Z are independent, where the precipitation transition probabilities are defined by the Bayesian model as described above and the infrastructure state transitions are deterministic and defined by the actions. We solve for the optimal polices and value function using backwards recursion.

The shortage cost component of the cost function is developed using a water resource system model that applies stochastic weather generation to the current precipitation state, generating monthly precipitation time series that force a rainfall-runoff model, which in turn forces a reservoir operations model and estimates shortages relative to demand. Shortage costs are assumed proportionate to the square deficit of water shortages. The approach follows Fletcher, Lickley, and Strzepek (2019) with minor improvements. Notably, operating policies are updated over time as the climate changes instead of using a fixed rule curve approach. Details on each model component are available in SI Sections S5-S8.

The infrastructure component of the cost function and the actions models two infrastructure alternatives: a static and flexible dam. Both dams are built at the start of the planning period and use an existing cost model based on reservoir volume. The static dam uses economies of scale through building a larger dam upfront that cannot be changed later in the planning period. In contrast, the flexible dam is built small initially, but has multiple expansion options that can be used once in the planning period, albeit for additional costs. Hence, expanding the flexible dam to an equivalent size of the static dam is more expensive, and so flexibility is traded off with economies of scale. Detailed cost model information is in SI Section S9.

We combine the high- and low-learning transition probabilities with the static and flexible infrastructure alternatives in our infrastructure planning SDP to obtain the optimal, i.e., lowest expected total cost, static and flexible infrastructure designs under our two climate learning scenarios. Then, we re-run our infrastructure planning SDP using the previously determined infrastructure designs to obtain the optimal dam policies, which includes whether to choose the static or flexible dam initially, and if we choose the flexible dam, if, when, and by how much to expand the dam’s capacity under our discretized state space.

Lastly, we use Monte Carlo simulation to test how the optimal dam designs and policies perform on cost and reliability metrics under our two climate learning scenarios. Through simulating 10,000 instances of possible time series of precipitation from the climate learning scenarios, and applying the optimal policies from the SDP, we develop distributions of the costs, reliability, and infrastructure planning decisions. To explore how the dynamics of learning and flexibility change under different climate simulations, we categorize the simulations into dry, moderate, or wet based on their end of century precipitation values. Details available in SI Figure S2.

2.6 Quantifying the Value of Learning for Flexibility

We quantify the value of learning for flexibility to understand how differences in learning about climate uncertainty affect the value of flexible water infrastructure. A high-learning climate may increase the value of flexibility because dry or wet climate simulations are more likely to continue in that direction, so optimal dam expansion decisions can be made earlier. Since the planning cost of a particular climate learning scenario is influenced by natural climate variability, e.g., how wet or dry the climate is, as well as how much it is possible to learn about the climate, we isolate the value of learning from climate variability. To understand the differences between high- and low-learning climate scenarios, we compare the costs of the flexible and static dams under the two climate learning scenarios, as shown in Figure 2b.

We quantify the value of learning for flexibility as the difference between the expected costs of the static and flexible dams under high- and low-learning scenarios, as shown in Equation 5:

$$A = \ Value\ of\ flexibility\ in\ high - learning\ climates = Cost_{stat,hi} - Cost_{flex,hi}$$

$$B = \ Value\ of\ flexibility\ in\ low - learning\ climates = \ Cost_{stat,low} - Cost_{flex,low}$$

Equation 5

This value is positive when static dam costs exceed flexible dam costs, as shown in Figure 2b.

3 Results

First, we present results from the exploratory Bayesian model for the high- and low-learning climate scenarios. Then, we present the results on the dam infrastructure decisions and costs using the infrastructure planning SDP for each climate learning scenario.

3.1 High- and Low-Learning Climate Scenarios

Figure 3 presents results from the exploratory Bayesian model, illustrating differences in simulated precipitation time series and learning rates between the high- and low-learning climate scenarios. This illustrates how new synthetic observations reduce uncertainty in long-term precipitation projections more with high-learning climates than low-learning climates. In panel a, under high learning, a drying or wetting trend in simulated precipitation near the beginning of the time series is likely to continue to end of century. In contrast, in panel b we see that under low learning, early trends do not always continue. We measure this using average one-lag autocorrelation values, which are 0.43 and 0.19 for high- and low-learning climate scenarios, respectively.

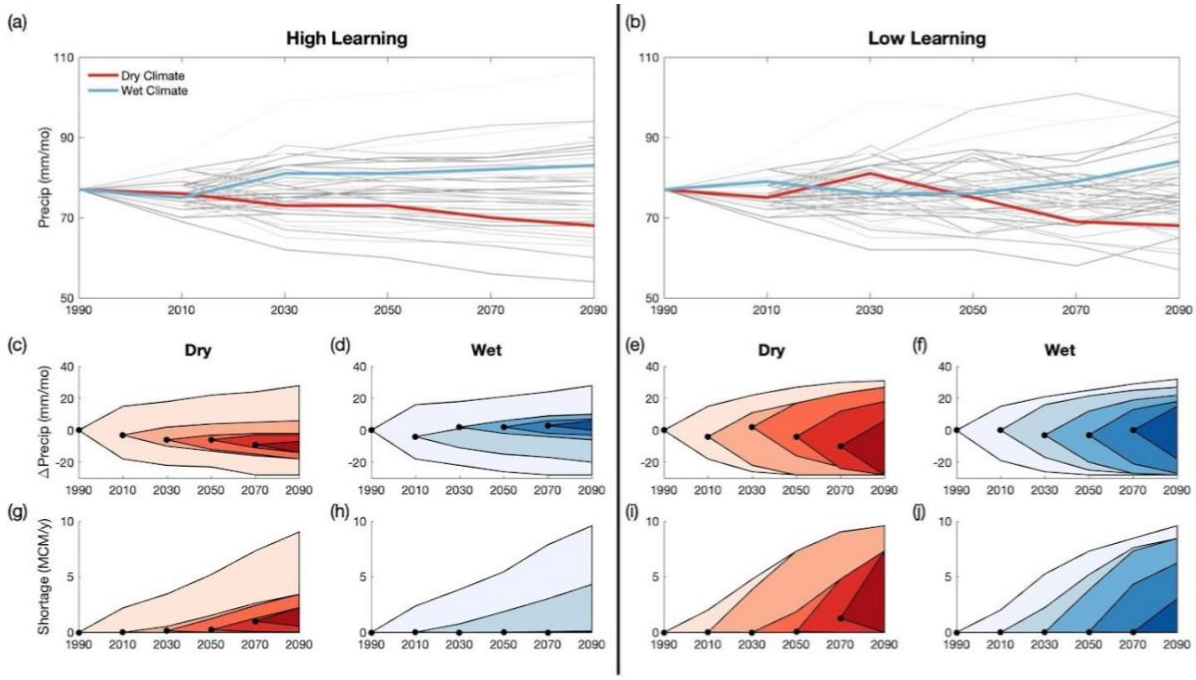

Figure 3. High- and low-learning climate sample precipitation and water shortage simulations. Sample simulations are shown for wet and dry realizations, defined by their end-of-century precipitation change. a-b) Sample precipitation simulations under high- and low-learning climate scenarios are shown in gray. Red and blue lines indicate samples shown in c-j. c-f) Sample precipitation instances with uncertainty bounds under high- and low-learning, dry and wet climate simulations. g-j) Sample water shortage instances with uncertainty bounds under high- and low-learning, dry and wet climate conditions. The specific simulation values are shown by the black points. As the shading gets darker, the observation time period progresses through the 21st century.

In panels c-f, we illustrate learning by observing precipitation uncertainty over time. In each panel, we simulate one precipitation time series, use it in the Bayesian model to update later projections, and show the resulting posterior distributions. In panels g-j, we show how this process propagates through the infrastructure model and leads to learning about shortage uncertainty, which is the metric we ultimately care about to meet water demands. High learning leads to large reductions in uncertainty in both precipitation and water shortages (panels c-d, g-h). In contrast, low learning leads to smaller reductions in precipitation uncertainty (panels e,f), but the impact on water shortage uncertainty varies across dry and wet simulations. Uncertainty in water shortages is reduced modestly in dry simulations (panel f) and greatly in wet simulations (panel j). This demonstrates a non-linear relationship between precipitation and water availability: above a certain precipitation threshold, enough water is available, and no water shortages incur. Since Figure 3 illustrates the dynamics of updating uncertainty using one realization of a time series, the optimization and simulation results, which use many realizations, are unchanged by the choice of time series here. SI Figure S3 highlights contrasting low-learning dry and wet realizations for reference.

Next, we use KL divergence to quantify the learning from additional precipitation observations, shown in Figure 4. The results confirm that the high-learning climate scenario leads to greater KL divergence values in simulated precipitation compared to low learning. The boxplots in panel a show the range of KL divergence values for simulated precipitation under high- and low-learning climate scenarios for different information years, using 1990 as the prior year and 2090 as the projection year. The distribution of KL divergence values is higher in the high-learning climate scenarios across all information years compared to the low-learning climate scenarios.

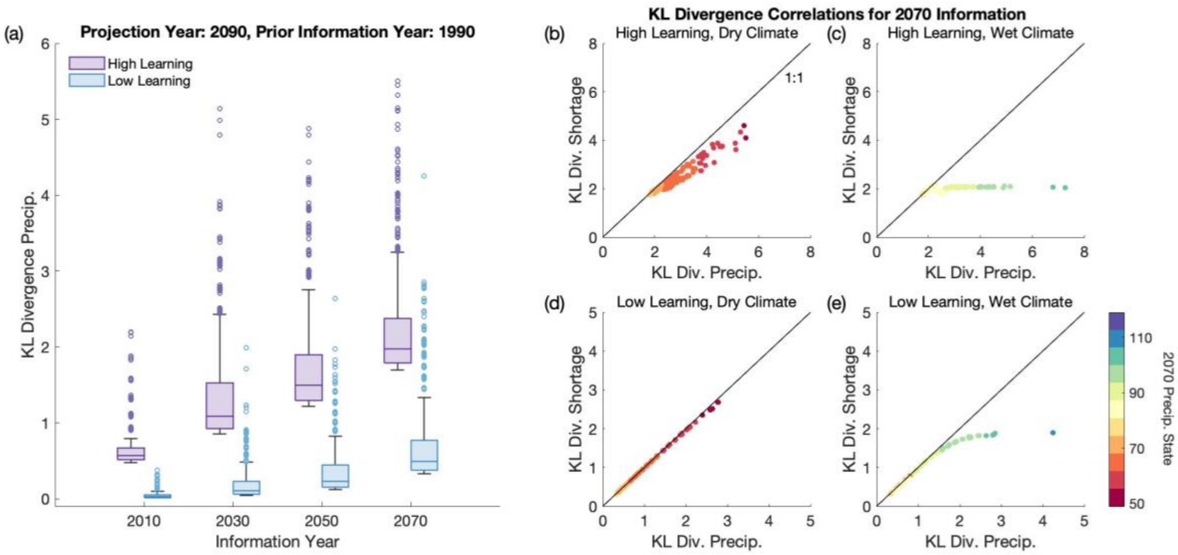

Figure 4. KL divergence results for high- and low-learning, wet and dry climate scenarios. A) Distributions of KL divergence values for precipitation across different information years for a prior information year of 1990 and a projection year of 2090. b-e) Correlations between KL divergence for precipitation and water shortages. The black lines show a 1:1 line for reference, and the points are colored by the 2070 precipitation state, which is the information year used here.

Panels b-e show the relationship between KL divergence values for precipitation and water shortages, and see how this relationship changes in high- vs. low-learning climates and wet vs. dry simulations. In wet simulations (panels c, e) KL divergence is sometimes lower for water shortages than for precipitation. Since water shortages do not occur in many wet simulations, the distributions of water shortage uncertainty have a low expected value, exhibit a small amount of uncertainty, and do not change much with additional observations. New information about precipitation and water availability is not valuable in this situation. In comparison, under a dry climate, the KL divergence values for water shortage have a linear correlation with the KL divergence values for precipitation, as seen by comparing the scatter plots to the black line with a slope of one. Therefore, under a dry climate we learn similar amounts about precipitation and water shortages.

3.2 Dam Infrastructure Decisions and Costs under High- and Low-Learning Climate Scenarios

After presenting our climate learning scenario results, we now explore the performance of the dam infrastructure alternatives for each climate learning scenario. We first quantify how high- and low-learning climates influence infrastructure decisions and costs across dry, moderate, and wet climate simulations and discount rates (Figure 5). The flexible dam is most valuable under wet climate simulations, where flexibility prevents overbuilding. Additionally, high-learning climate scenarios lead to decreased water shortages and costs in wet and moderate climate simulations because precipitation trends earlier in the planning period are more consistent and predictable throughout. However, under dry climate simulations, both high- and low-learning climate scenarios have similar water shortage penalty costs. This is because under dry climates, learning is not particularly valuable as natural water availability simply does not meet demand regardless of the infrastructure decision.

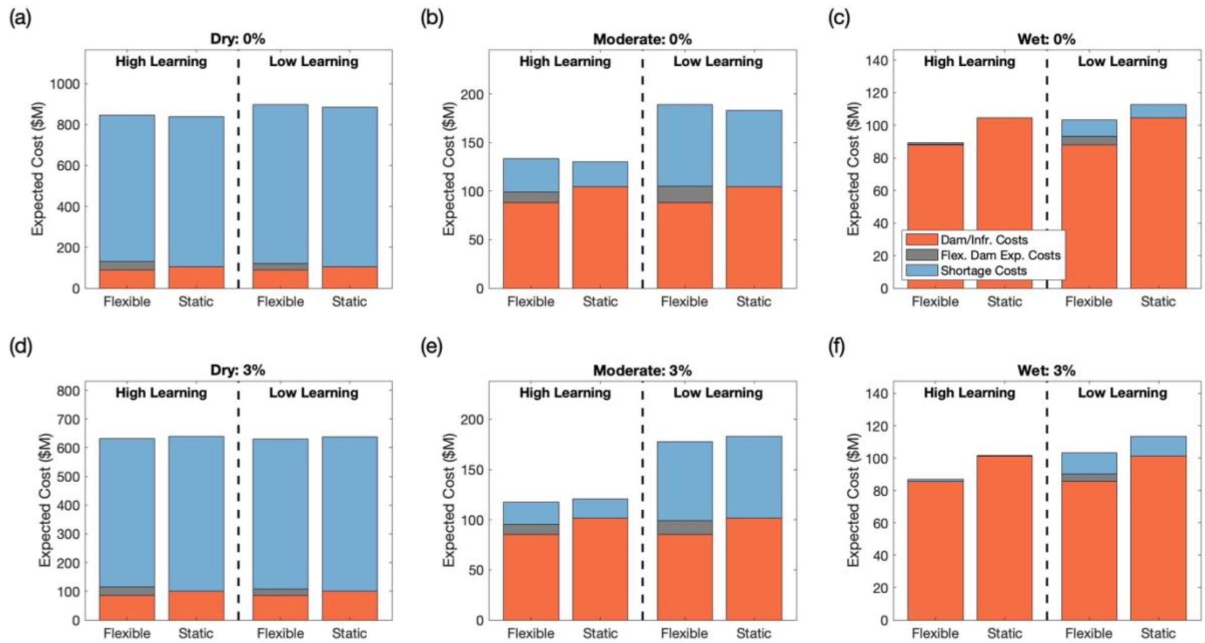

Figure 5. Expected costs across 10,000 simulations of optimal planning policies for flexible vs. static dams and high- vs. low- learning climate scenarios. Bars show the portion of the costs associated with dam infrastructure (orange), dam expansion (gray), and water shortage penalty costs (blue). Costs are compared under 0% (a-c) and 3% (d-f) discount rates; and dry (a, d), moderate (b, e), and wet (c, f) precipitation simulations. The vertical axis scale varies across panels to facilitate readability of results.

With zero discounting in panels a-c, the expected cost of the flexible dam is less than the expected cost of the static dam only for wet climate simulations, where the costs are driven by infrastructure costs as water shortage penalty costs are low. The static dam slightly outperforms the flexible dam for dry and moderate climate simulations. This is because the additional costs to expand the flexible dam are not fully mitigated through decreased water shortage penalty costs. There are two main reasons for this. First, since the flexible dam is initially smaller than the static dam, drier climate simulations near the beginning of the planning period may lead to larger water shortage penalty costs initially. Second, even once the flexible dam expands, lack of water availability in drier simulations diminishes the value of increasing the amount of dam storage. SI Figure S4 illustrates this result by presenting shortage costs of different dam sizes for different precipitation conditions. With a discount rate, investments later in the simulation horizon are cheaper. Flexible dams both delay infrastructure design decisions to learn about uncertainty and delay investments, which decreases their net present cost. For a 3% discount rate (panels d-f), the expected cost of the flexible dam is always less than that of the static dam, though still similar in magnitude.

Next, we quantify the value of flexibility under high- and low-learning climate scenarios and contrasting precipitation simulations. This is seen in Figure 6, which illustrates distributions of the cost difference between flexible and static alternatives under a range of simulations. Flexibility is most valuable for wet simulations when water shortage penalty costs are low, and we do not need to expand the flexible dam. But many negative outliers occur, especially with a low learning climate, where overbuilding is more likely, which occurs when the flexible dam expands even though a larger dam is not ultimately needed. Higher discount rates increase the value of flexibility. With no discounting in panel a, the value of flexibility is often negative under moderate and dry scenarios, although it is less negative under high-learning compared to low-learning climate scenarios. With the 3% discount rate in panel b and all climate simulations, the distributions for the value of flexibility are mainly positive.

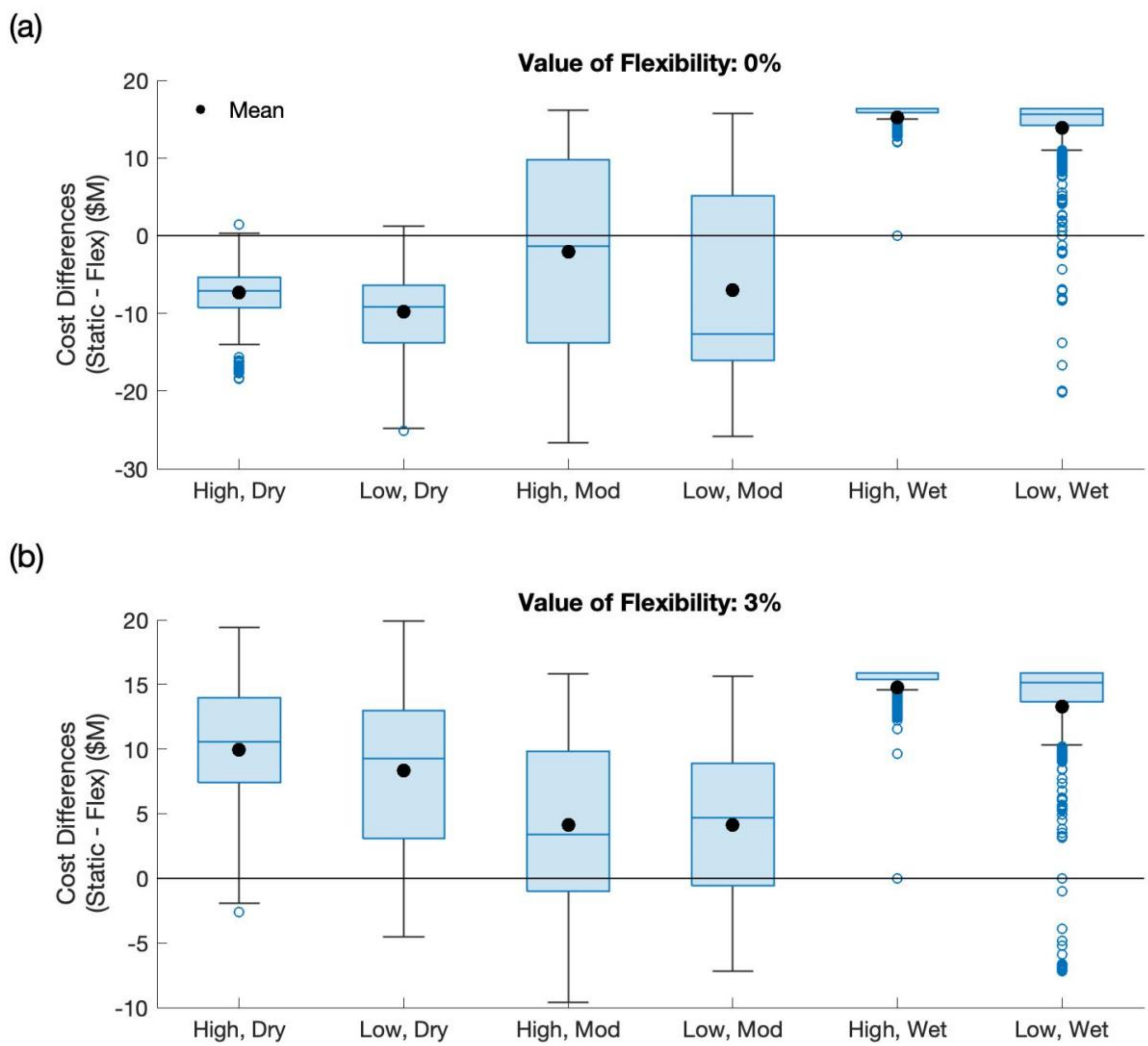

Figure 6. Distributions of the value of flexibility across 10,000 precipitation simulations under a) 0% and b) 3% discount rates. Both panels show the distributions of cost differences between the static and flexible dams under high- and low-learning climate scenarios; and dry, moderate, and wet simulations. The black points show the mean of the distributions.

Another interesting result in Figure 6 is that there are different trends in the distributions with the 0% and 3% discount rates. With the 3% discount rate in panel b, cost differences between the static and flexible dams are, on average, greater under dry conditions than moderate conditions; this is reversed for the 0% discount rate in panel a. An explanation for this is that with the 3% discount rate for both high and low learning, a larger fraction of simulations where the flexible dam is chosen expand to the 140 or 150 MCM dam, which exceeds the static dam of 130 MCM, compared to the 0% discount rate.

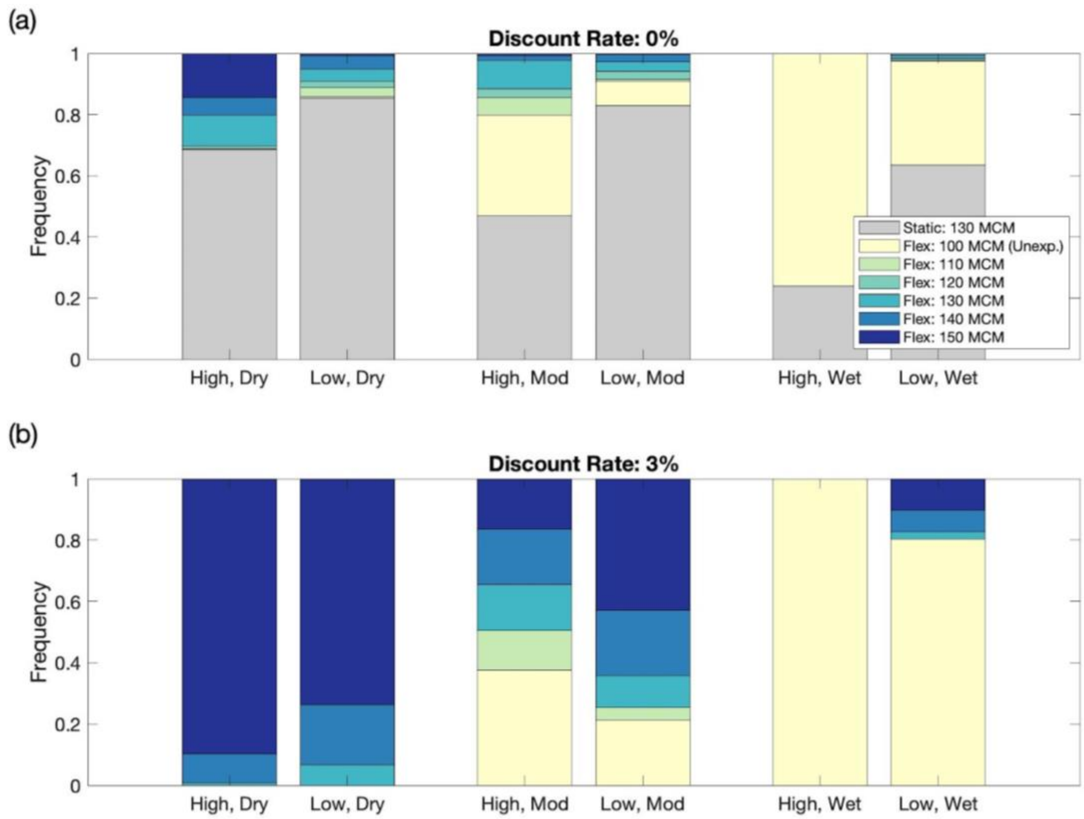

Figure 7. Static and flexible dam infrastructure and expansion decisions under a) 0% and b) 3% discount rates. The shaded colors show the frequency that the static dam is chosen (gray) compared to the flexible dam (colors). As the shading gets darker, the flexible dam expands to a larger volume.

In Figure 7, we illustrate the frequency with which the flexible or static dam is selected, and the flexible dam is expanded. In the high-learning climate scenario, the flexible dam is selected more frequently, and the least-regret expansion decision is selected more frequently compared to the low-learning climate scenario. In panel a under the 0% discount rate, the flexible dam is selected 17% and 40% more frequently with high learning than low learning, for dry and wet climate simulations, respectively. As conditions progress from dry to wet, the flexible dam is chosen more frequently for both high- and low-learning climate scenarios. For both discount rates, more overbuilding (dam expansions under wet conditions) and underbuilding (less and smaller dam expansions under dry conditions) occurs with low learning, illustrating the ability of the optimal policy to choose low-regret actions more effectively in the high-learning climate scenario.

Finally, we compare KL divergence with dam infrastructure decisions in Figure 8 to assess the relationship between the amount of learning about climate uncertainty and flexible planning. More learning leads to less over- or underbuilding, and hence, better flexible dam expansion decisions. First, panels a and c show that the relationship between KL divergence for precipitation and the 2090 precipitation state has a “U” shape, with more extreme value precipitation simulations having higher KL divergence values. Panels b and d show a similar relationship between KL divergence for water shortages under dry 2090 precipitation states. However, higher KL divergence values for water shortages do not occur in more extreme wet precipitation states. As discussed in Figures 3 and 4, above a certain amount of precipitation, water shortages do not occur anyway.

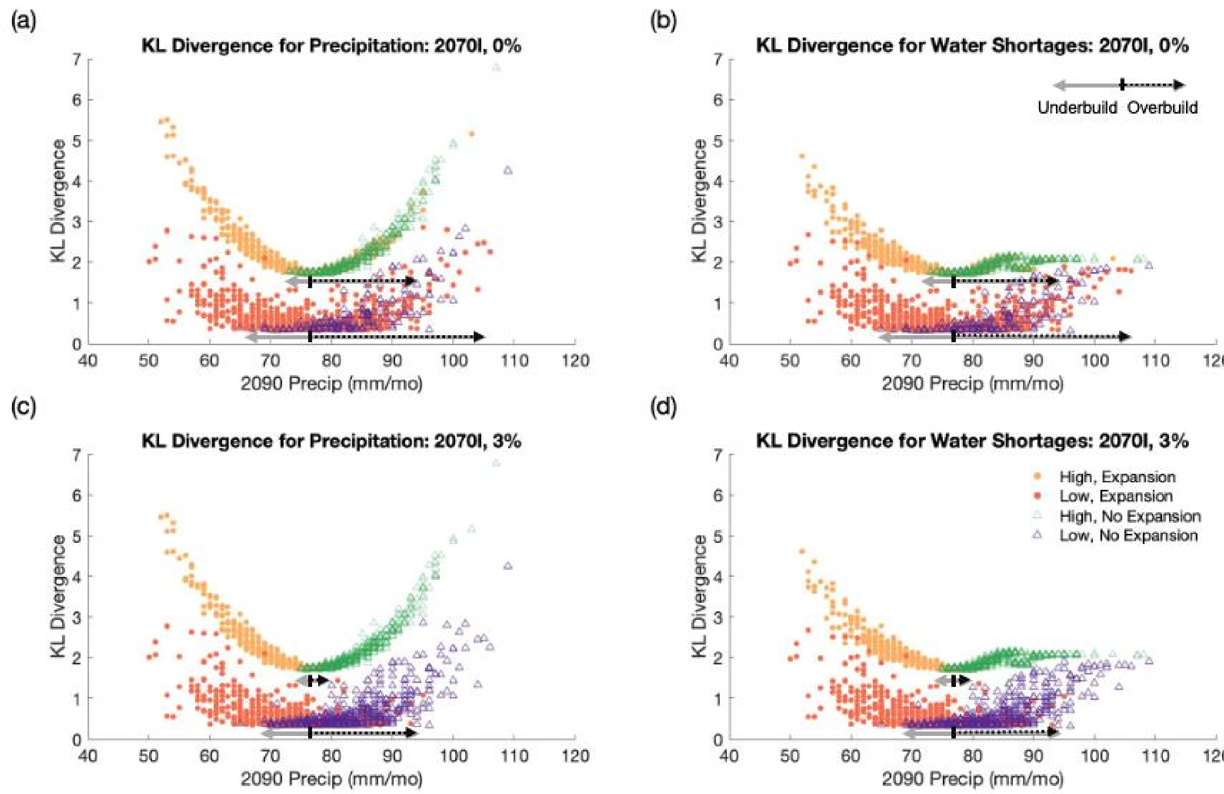

Figure 8. KL divergence scatter plot for simulations with and without dam expansion under a-b) 0% and c-d) 3% discount rates. The four scatterplots show the correlation between KL divergence for a) and c) precipitation and b) and d) water shortages, compared to the 2090 precipitation state. The different colors and shapes show high and low learning with and without dam expansions from the simulation model.

In intermediate precipitation ranges, which we call “transition zones,” samples occur with and without dam expansion. We call policies with unexpanded dams in the left portion of the transition zone “underbuilding,” highlighted with the gray arrows when we have dry 2090 precipitation states, but no dam expansion. We call policies with expanded dams in the right portion of the transition zone “overbuilding,” highlighted with the black arrows when we have wet 2090 precipitation states, but dam expansion. The black vertical lines highlight the initial precipitation state in 1990. With low-learning climate scenarios, transition zones are much larger than with high-learning scenarios. This highlights how more uncertainty in future climate and water availability may lead to less optimal dam infrastructure decisions. The transition zones under low learning are larger on both sides—we have both drier states where the flexible dam does not expand (underbuilding) and wetter states where the flexible dam does expand (overbuilding).

Additionally, larger transition zones occur with a zero discount rate in panels a and b, compared to a 3% discount rate in panels c and d. This is mainly driven by a larger range of precipitation states with overbuilding. One hypothesis as to why more overbuilding, but not more underbuilding, occurs with zero discounting is because discounting incentivizes delayed investment. Therefore, with discounting, the flexible dam is more likely to expand later in the planning period because delayed investment is less costly. Without discounting, the flexible dam is more likely to be expanded early in the planning period, which could lead to overbuilding.

4 Discussion and Conclusions

In this work, we develop a framework to assess the value of learning in flexible water supply infrastructure planning. An exploratory Bayesian modeling approach is used in which we adjust the variance of the likelihood function to develop contrasting scenarios where we can learn a high or low amount about future climate uncertainty through observation. We assess the value of a flexible water supply infrastructure development approach in different climate learning scenarios across a range of precipitation conditions. We quantify the value of learning for flexibility by first comparing the differences in costs between the static and flexible dams, and then comparing those differences across high- and low-learning climates.

Our results demonstrate that learning about uncertainty can improve the effectiveness of flexible planning in providing low-cost, reliable supply in some but not all conditions. Our Bayesian modeling results demonstrate that near-term precipitation observations provide more information about long-term precipitation, leading to updated precipitation projections substantially narrower than prior estimates. However, these reductions in uncertainty propagate non-linearly to water shortage uncertainty, driven by thresholding behavior. Uncertainty in water shortage projections is reduced faster than precipitation projections in wetter conditions and slower in drier conditions.

Similarly, the value of flexibility – and the value of learning for flexibility – is only consistently positive in wet precipitation simulations. In these cases, flexibility allows the planner to build a smaller dam at the outset of the planning period compared to the static development approach and prevents overbuilding of unnecessary new infrastructure. This effect is larger in the high-learning climate scenario, where the optimal policy is more consistently able to identify the least-regret option. In contrast, with dry climate conditions, flexibility has limited value because water reliability is constrained by limited water available to refill the reservoir, not limited reservoir storage size. Therefore, regardless of how much learning about future climate uncertainty is feasible, there is limited benefit to flexibly expanding dam storage as the climate dries because the reservoir is unlikely to refill and utilize additional storage capacity.

Since the specific results we highlight depend on the assumptions and context of our case study, further sensitivity and uncertainty analysis would help further build theory on the conditions under which flexibility is most valuable. Applying this approach to regions with different hydroclimate conditions may lead to greater value of learning and flexibility in drying conditions. While we focus on long-term precipitation trends, more work can be done assessing impacts of shorter-term uncertainty in precipitation variability, water demands, and dam costs on total system costs and the value of flexibility. For example, we hypothesize that larger monthly variability in precipitation or changes in seasonality could increase the value of learning and flexibility. This is because greater variability would require more storage capacity to maintain reliable water supply. Therefore, large increases in dam storage would more effectively reduce shortages compared to our current study. Counterintuitively, it may be that a case study with less uncertainty in precipitation would see greater value from learning because a single flexible infrastructure design would be able to adapt more effectively to the full range of possible outcomes. Additionally, while we focus on uncertainty in long-term precipitation trends, demand uncertainty due to population growth and economic conditions is likely similarly influential. Future work could expand the SDP framework to add additional system states for different water demand conditions and incorporate learning about demand trends.

Further work also could assess other forms of both learning and flexibility. This study focuses on learning by observation. We could also explore learning by model improvement by comparing precipitation projections from different climate model generations (e.g. CMIP3 vs CMIP5 vs CMIP6). Similarly, we could explore learning by information collection in a region with multiple streamflow gauges by holding out then adding additional gauge data. These approaches may show sharper changes in uncertainty over time rather than the slow gradual changes here by observation. This could potentially increase the value of learning for flexibility. Similarly, this study focuses on flexibility in infrastructure design through capacity expansion. Future work could compare flexibility in planning processes and in operations to compare how different forms of flexibility interact with different learning scenarios.

Our methodological framework to quantify climate learning scenarios and to connect learning with the value of flexibility can be extended to other infrastructure planning domains. Climate change uncertainty impacts many planning fields, such as energy (Cohen et al., 2022; Schaeffer et al., 2012), transportation (Dewar et al., 2008), and natural resources management (West et al., 2009). Each of these sectors necessitates expensive infrastructure and planning investments based on uncertain future conditions. Indeed, annual climate change adaptation costs in lower-income countries are expected to increase from approximately 70 billion USD today to between 280 and 500 billion USD in 2050 (United Nations Environment Programme, 2021). Through our methodology to quantify learning about future uncertainty and improve the usefulness of flexible infrastructure, we improve the theory and approaches that can be used for adaptive planning. This can support cost-effective climate adaptation, helping target scarce resources where they are needed most.

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Open Research

All data and software used this study can be found at (Skerker, 2023).

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Supporting Information References