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Learning and flexibility for water supply infrastructure planning under groundwater resource uncertainty

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Abstract

Water supply infrastructure planning in groundwater-dependent regions is often challenged by uncertainty in future groundwater resource availability. Many major aquifer systems face long-term water table decline due to unsustainable withdrawals. However, many regions, especially those in the developing world, have a scarcity of groundwater data. This creates large uncertainties in groundwater resource predictions and decisions about whether to develop alternative supply sources. Developing infrastructure too soon can lead to unnecessary and expensive irreversible investments, but waiting too long can threaten water supply reliability. This study develops an adaptive infrastructure planning framework that applies Bayesian learning on groundwater observations to assess opportunities to learn about groundwater availability in the future and adapt infrastructure plans. This approach allows planners in data scarce regions to assess under what conditions a flexible infrastructure planning approach, in which initial plans are made but infrastructure development is deferred, can mitigate the risk of overbuilding infrastructure while maintaining water supply reliability in the face of uncertainty. This framework connects engineering options analysis from infrastructure planning to groundwater resources modeling. We demonstrate a proof-of-concept on a desalination planning case for the city of Riyadh, Saudi Arabia, where poor characterization of a fossil aquifer creates uncertainty in how long current groundwater resources can reliably supply demand. We find that a flexible planning approach reduces the risk of over-building infrastructure compared to a traditional static planning approach by 40% with minimal reliability risk (<1%). This striking result may be explained by the slow-evolving nature of groundwater decline, which provides time for planners to react, in contrast to more sudden risks such as flooding where tradeoffs between cost and reliability risk are heightened. This Bayesian approach shows promise for many civil infrastructure domains by providing a method to quantify learning in environmental modeling and assess the effectiveness of adaptive planning.

1. Introduction

Many groundwater systems around the world are facing depletion due to unsustainable withdrawals (Wada *et al* 2010, Bierkens and Wada 2019). Water planners in these regions face the challenge of developing policies, infrastructure, and management strategies to ensure the long-term reliability of water supplies. Planning relies on modeled projections of the impact of pumping on the groundwater system under different management approaches. However, data scarcity often challenges groundwater modeling, especially in developing countries (van Camp *et al* 2013, Jha and Chowdary 2007). This can create substantial uncertainty in forecasts of groundwater availability (Yoon *et al* 2013). Furthermore, the same

regions that are data scarce are also often budget constrained, and therefore often cannot simply develop alternative water infrastructure or supplies as a robust strategy for maintaining reliability in the face of an uncertain future (World Bank Group 2015). Therefore, adaptive (also known as flexible) infrastructure planning and design approaches which allow planners to learn over time as more information is collected and react accordingly may be a more feasible strategy to maintaining reliable water supply (Beh *et al* 2015, Fletcher *et al* 2017).

Groundwater resource assessment often faces large uncertainty due to high spatial heterogeneity in groundwater aquifers combined with limitations in data collection and access (Ojha *et al* 2014). This makes it difficult to project long-term water table decline or estimate sustainable yields. Previous studies have used Bayesian calibration and Monte Carlo methods to estimate uncertainty in key parameters like hydraulic conductivity (K) and storativity (S) as well as uncertainty in conceptual model structure (Refsgaard *et al* 2012). Recent work has also shown that collecting new data to update uncertainty estimates can substantially reduce predictive uncertainty (Feyen and Gorelick 2005, Dausman *et al* 2010, Neuman *et al* 2012, Xue *et al* 2014). It is critical to address predictive uncertainty in groundwater management decisions (Delottier *et al* 2017), such as importing water supplies to offset groundwater withdrawals (Sreekanth *et al* 2015), optimizing pumping rates (Baú 2012), and applying withdrawal restrictions (Theodossiou and Fotopoulou 2015).

Adaptive planning has been promoted in many areas of environmental management including water resources (Pahl-Wostl 2007), climate adaptation (National Research Council 2004), conservation (Williams and Johnson 2013), and forest management (Stephens *et al* 2010) as a way to respond to uncertainty as learning occurs over time. Several methods for decision-making under uncertainty have been applied to adaptive water infrastructure planning, including dynamic adaptive policy pathways (Haasnoot *et al* 2013, Kwakkel *et al* 2015, Stephens *et al* 2018), robust decision making (Groves *et al* 2015, Kwakkel *et al* 2016), and decision-scaling (Poff *et al* 2015). Additionally, a few recent studies have developed Bayesian methods for adaptive planning, either in combination with non-stationary stochastic dynamic programming (SDP) (Hui *et al* 2018, Fletcher *et al* 2019) or decision-scaling (Taner *et al* 2019). Most adaptive approaches identify thresholds that can be used to trigger additions of new infrastructure. Engineering options analysis (EOA), which has also been applied to water infrastructure (Jeuland and Whittington 2014, Fletcher *et al* 2017, Erfani *et al* 2018, Fletcher *et al* 2019) additionally assesses in advance whether and under what conditions upfront investments to enable future flexibility (e.g. extra structural support or permitting for future expansion) are worthwhile. This is important because infrastructure development requires large investments upfront that last for multiple decades, and flexible approaches such as modular or staged infrastructure additions can ultimately be more expensive than traditional large scale projects (de Neufville and Scholtes 2011).

This study develops a planning framework that connects opportunities to learn about groundwater resource uncertainty to adaptive infrastructure planning. It integrates Bayesian learning on a groundwater model with a multistage stochastic planning model as a way to assess: (1) the potential for future observations of hydraulic head to reduce predictive uncertainty in groundwater availability and (2) the effectiveness of adaptive infrastructure planning in responding to updated uncertainty to meet performance goals under a variety of planning assumptions. To do this, we use Bayesian inference to estimate how different potential future drawdown observations, which correspond to groundwater level states in the stochastic planning model, would update groundwater resource projections if they were observed. These updated aquifer predictions characterize the uncertainty in a stochastic dynamic program (SDP), which develops adaptive infrastructure policies. EOA is then used to evaluate and compare the trade offs in using a flexible infrastructure development approach in comparison to a traditional static planning approach.

To our knowledge, this is the first study to link predictive groundwater uncertainty to adaptive infrastructure planning. We also make methodological advancements from previous methods that integrate non-stationary SDP and Bayesian methods to assess adaptive planning in water resources. Hui *et al* (2018) assume that future hydrology takes the form of one a few fixed scenarios of streamflow distributions; Bayes' theorem is to estimate the probability of each scenario. Fletcher *et al* (2019) uses Bayesian model uncertainty methods applied to an ensemble of climate model projections to both develop and update distributions. However, this approach is limited by the number of climate model projections available. In this study, we further extend the Bayesian framework of Fletcher *et al* (2019) by embedding a hydrological model (here, the groundwater model MODFLOW), allowing us to use the hydrological model to specify the likelihood function directly and not rely on a small ensemble of projections. This is made computationally tractable using a statistical surrogate for MODFLOW in the form of an artificial neural network (ANN).

We demonstrate a proof-of-concept for Riyadh, Saudi Arabia (KSA) where decades of large withdrawals from non-renewable aquifers have led to substantial decline in hydraulic head (which determines the height of water in a well). Eventually, maintaining current withdrawal rates with existing pumping infrastructure will no longer be possible. However, these aquifers are poorly characterized, leading to

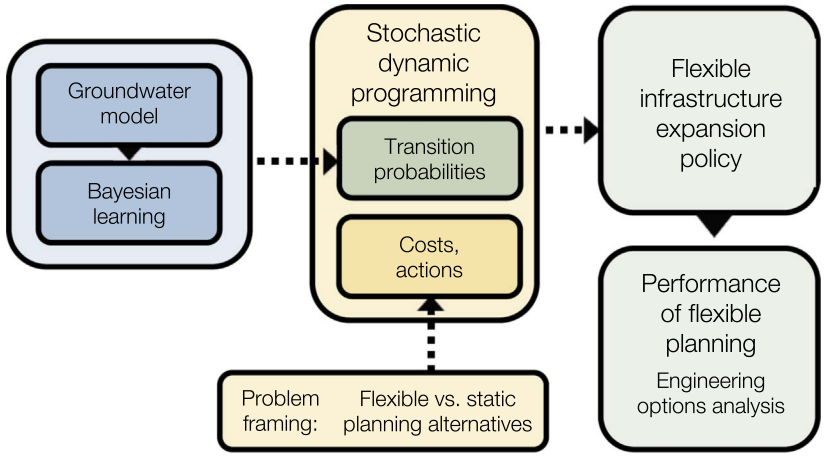

Figure 1. Schematic of method used to develop and evaluate flexible infrastructure expansion policies that account for the potential to learn about uncertainty over time. The method integrates a groundwater model into a multi-stage stochastic dynamic program. Bayesian inference is used to characterize the transition probabilities; each state of the SDP is treated as a hypothetical future observation and used to update the prior parameter distribution using Bayes' theorem. EOA is used to assess the performance of the flexible alternative and compare to traditional static planning alternatives.

substantial uncertainty in when a transition to alternative supply such as desalination will be necessary. As Riyadh's planners consider expensive investments in desalination, planners can ensure reliability without over investment by monitoring head decline over time, updating predictions, and adapting as needed. We evaluate a flexible planning approach in which, rather than deciding upfront whether or not to develop new infrastructure over a 30 year planning period, the decision to develop infrastructure is deferred. However, a small upfront investment is made to enable new infrastructure to be developed quickly if and when it is needed.

2. Methods

The planning framework is implemented using five key steps, illustrated in figure 1, and detailed in the following sections.

1. Frame planning problem and develop flexible infrastructure planning approaches that have the potential to mitigate the impacts of uncertainty.
2. Develop a groundwater model and characterize parameter uncertainty. Use Monte Carlo simulation across the uncertain parameters to characterize prior uncertainty in hydraulic head predictions.
3. Use Bayes' theorem to update priors using potential future observations. The resulting posteriors characterize the transition probabilities in a non-stationary SDP.
4. Formulate and solve the SDP to develop flexible water infrastructure policies that account for the potential to learn about groundwater uncertainty in the future.
5. Evaluate flexible infrastructure policies against key planning metrics including reliability and cost and assess trade offs to traditional static planning approaches using EOA.

2.1. Problem framing and flexible plan development

First, we assess the planning context, including: infrastructure projects under consideration for development, key objectives identified by planners, and the groundwater resource uncertainty. We then develop potential flexible strategies that may mitigate the impacts of the uncertainty.

Our proof-of-concept considers the region of Riyadh, Saudi Arabia. Riyadh had a population of 7.7 million in 2014 and is growing at 3.5% a year (Saudi Arabian Gerenal Investment Authority 2014). A highly arid region receiving on average only 24 mm of rainfall per year (Dannatt and Paszkowksi 2017), Riyadh's water needs are primarily supplied by seawater desalination piped from the Arabian Gulf (1.4 MCM/d in 2016) and groundwater extraction, primarily from deep fossil aquifers (1.07 MCM/d in 2016) (Dannatt and Paszkowksi 2017). The Minjur aquifer comprises the largest share of groundwater extraction, supplying about 300 000 $m^3\ d^{-1}$, and is therefore the focus of our study.

The Minjur has faced substantial drawdown due to the combination of large withdrawals and minimal recharge. The government has announced plans to: reduce net demand per capita, add additional desalination capacity, increase reuse of treated wastewater, and maintain current groundwater withdrawals (Al-Saud 2013, Dannatt and Paszkowksi 2017). However, as the Minjur continues to drawdown, withdrawals will eventually become technically infeasible for existing pumping infrastructure, rendering the aquifer effectively depleted. Large uncertainties in both

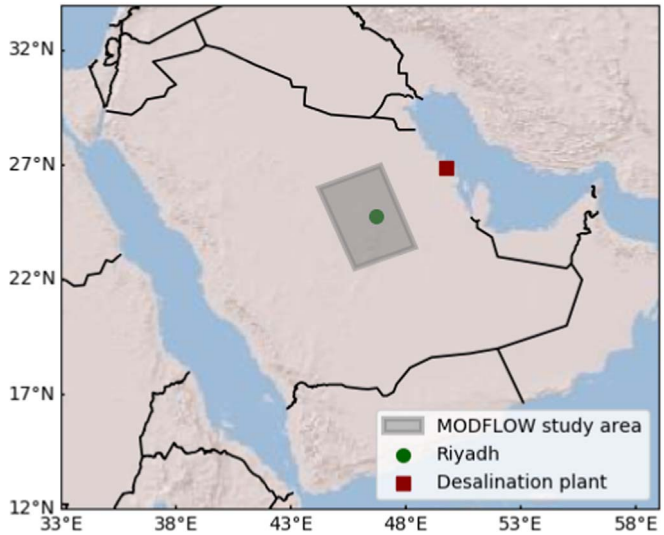

Figure 2. Study area with groundwater model grid location, Riyadh city center, and location of proposed desalination plant in Jubail.

aquifer storativity and hydraulic conductivity put estimates of the time to depletion ranging from years to decades. Because precipitation is limited and the Minjur is a confined fossil aquifer, recharge is low; therefore, precipitation variability and climate change are not significant uncertainties in groundwater resource assessment.

Given the government's focus on desalination, we model the development of new desalination infrastructure to replace withdrawals from the Minjur. Because the salient uncertainty is the timing of aquifer depletion, we consider flexibility in the timing of new desalination development. In particular, we consider a flexible approach in which planners observe aquifer drawdown over time and decide if and when to build additional capacity based on updated predictions of the time to depletion. To facilitate this approach, planners make advance preparations in the form of design, siting, permitting, initial contracting, etc so that infrastructure can be developed quickly in two years to avoid reliability outages if and when it becomes clear that it is needed. We contrast this with a traditional, static planning approach in which water planners decide at the beginning of a 30 year planning period whether or not to build new desalination infrastructure. We assume constant withdrawals due to our methodological focus on groundwater uncertainty.

2.2. Characterizing predictive uncertainty using a groundwater model

We model the impacts of groundwater withdrawals on the Minjur aquifer in the Riyadh region; the study area is shown in figure 2. A groundwater simulation model is used to predict hydraulic head h in the future as a function of an uncertain input parameter vector θ and recharge and withdrawals W from 120 major pumping wells. In our application, h is the hydraulic head in a single representative well at the center of Riyadh, where pumping is the most intense, drawdown in the aquifer is greatest, and therefore pumping is likely to be constrained first. θ comprises the K and S of a confined aquifer. We use the finite difference groundwater model MODFLOW (Harbaugh 2005), and train an ANN on output from MODFLOW to serve as a computationally efficient statistical surrogate

$$h(t) = g[\theta, W, t] + \epsilon. \tag{1}$$

As in many regions in the developing world, historical data on hydraulic head in the Minjur is limited yet planning decisions must still be made. The best information available both to us and local city planners is an ongoing government hydrogeological study, which places estimates for K and S ranging from 1.39×10^{-5} m s^{-1} to 5.31×10^{-4} m s^{-1} and 1.00×10^{-4} to 1.12×10^{-3} respectively based on 61 reported measurements (Deutsche Gesellschaft fur Internationale Zusammenarbeit (GIZ) and Dornier Consulting International (DCI) 2016). Given this context, we have chosen to use these estimates to characterize uncertainty in K and S directly. Because of data limitations and for simplicity, we assume these parameters are homogeneous throughout the aquifer. While the assumption of a homogeneous unit can have impact on estimated hydraulic head depending on the hydrogeology (Zhang *et al* 2006), it is commonly applied in regional studies and is less impactful given our focus on long-term basin decline (Zhang *et al* 2006). We fit prior probability densities using maximum likelihood estimation based on the assumption that K is lognormally distributed (Freeze and Cherry 1979) and assume S uniform, representing an uninformed prior. The priors are modeled as uncorrelated given the absence of information about their correlation. These assumptions do not apply to the posterior estimates. Additionally, we tested the impact of using a prior for K (chosen because the

hydraulic head estimates are more sensitive to K than S) with half the variance; the posteriors show negligible change (see SI figures 4 and 5 available online at stacks.iop.org/ERL/14/114022/mmedia). This suggests the initial uncertainly is so large that the prior is uninformative and the posteriors are driven more by the observations. We additionally assume the errors ϵ independent and normally distributed with variance 5 m. This is a simple but common assumption to demonstrate the method; more sophisticated likelihood functions can be used in future work (Schoups and Vrugt 2010).

The conceptual model, finite difference grid design, and boundary conditions used in the MODFLOW model were taken from a previous USGS study of the Minjur (Williams and Al-Sagaby 1982). Note that because the aquifer here is confined and K and S assumed constant, a simple analytical groundwater model would have sufficed for our methodological proof-of-concept. We choose to use a numerical model and statistical surrogate to demonstrate that this approach is readily generalizable to more complex groundwater models in the future; this is important given that computational constraints have limited researchers from embedding numerical groundwater in stochastic optimization models in the past (Yeh 2015). Further details on the groundwater model, including ANN statistical surrogate, are available in the supporting information (SI).

Applying Monte Carlo simulation, we sample from $p(\theta)$ and $p(\epsilon)$ and run the groundwater model for each sample to characterize prior estimates for $h(t)$. We take the range of the $h(t)$ samples and discretize it at 1 m to create $h_{dis}(t)$. $h_{dis}(t)$ serves both as the set of groundwater states in the SDP and also as potential future observations in the Bayesian inference.

2.3. Bayesian learning using potential future groundwater observations

The transition probabilities in the SDP are characterized using Bayesian inference to reflect what will have been learned about future uncertainty if a particular groundwater state is reached in the SDP. For example, if the prior estimate for $h(t)$ had a median drawdown of 30 m after 10 years, but only 15 m were actually observed, an updated distribution for the following 20 years would show slower rates of drawdown than originally estimated.

$p(\theta)$ serves as the prior parameter distribution. The observation used to update the prior is taken from $h_{dis}(t)$; all values in $h_{dis}(t)$, which correspond to the state values for head in the SDP, are used in turn to calculate posterior distributions and therefore transition probabilities for each possible state in the SDP. The likelihood function $p(o \mid \theta)$ is characterized using equation (1). Numerical integration is used to estimate the posterior

$$p(\theta \mid o) = p(o \mid \theta)^{*} p(\theta)/p(o) \qquad o \in h_{dis}(t). \tag{2}$$

2.4. Developing flexible groundwater management policies using SDP

Next, we use the SDP to derive adaptive control policies for when to add desalination capacity as a function of the groundwater state and time period. The use of this adaptive policy is then compared to a static approach.

The objective of a SDP is to minimize the sum of the current costs plus the expected future costs over a set of possible actions $a(t)$. The expected future costs are calculated using the transition probabilities $p(s(t+1) \mid s(t), a(t))$ which describe the probability of being in a certain state in the next time period given the current state and action. In our application, the transition probabilities include the probability distribution of drawdown in head in the next time period given the head today and pumping rate as well as deterministic transitions reflecting planned and added capacity. We assume the groundwater transition probabilities are independent of the capacity transitions and therefore, $p(s(t+1) \mid s(t), a(t))$ is estimated as the product of these two state transition vectors. The groundwater transition vector $p(h(t+1) \mid h(t), a(t))$ is given by $p(h(\theta) \mid o = h(t))$ when $a(t)$ reflects pumping is on. $p(h(\theta) \mid o = h(t))$ is calculated by applying the groundwater model, which estimates $h(\theta)$, to the posterior samples of $p(\theta \mid o)$ from equation (2). By using non-stationary transition probabilities, in which the distribution for head changes over time as $h(t)$ in later time periods tells us more about the drawdown rate, we take into account the potential to learn about predictive uncertainty.

Discussions with planners indicate that the most immediate threat to current withdrawals is the technical ability of current pumping infrastructure to continue to operate if hydraulic head goes below approximately 300 m below land surface. Therefore, we impose a depletion depth of 50 m; beyond this limit pumping is infeasible, and planners must either supply water from new sources or incur penalties for unmet demand.

With the transition probabilities now characterized, the SDP can be formulated. The objective is given by the Bellman equation:

$$V(s, t) = \underset{a \in A}{\operatorname{argmin}}\, C(s(t), a(t), t) + \gamma \sum_{s \in S} p(s(t+1) \mid s(t), a(t)) {}^{*} V(t+1, s(t+1)), \tag{3}$$

where $V(s, t)$ is the optimal action for state s at time t, C is the cost including shortage damages of the current time period, γ is the discount rate, a and is an action taken from the set A of possible actions. The actions here are infrastructure decisions undertaken by the

water planner, primarily the decision to add desalination capacity. Costs are a function of the current state, time period, and action. They include capital and operating costs of desalination infrastructure, groundwater pumping, and shortage penalties if the depletion depth is reached without new desalination capacity being finished. Groundwater pumping costs are also included and increase with depth to reflect both increasing pumping energy required and degrading water quality with depth. Details available in the SI.

2.5. Evaluating flexible groundwater management strategies using EOA

Finally, we apply Monte Carlo simulation to generate many possible time series of groundwater drawdown and depletion times. In each simulated time series, we assess the performance of the flexible and static planning approach on two key performance metrics, cost and reliability, and assess the tradeoffs for planners in taking each approach. This effectively serves as a validation of the adaptive policies developed by the SDP in many different possible realizations of uncertainty (Robinson and Herman 2019).

3. Results

First, we examine the potential for Bayesian learning about predictive groundwater uncertainty by simulating potential future observations. Then, we demonstrate the impact of integrating this learning into the stochastic planning model and deriving the adaptive infrastructure development policies. Finally, we evaluate the adaptive planning approach using EOA.

3.1. Groundwater Bayesian learning

Figure 3 illustrates the Bayesian learning about K and S and its impacts on hydraulic head and water shortage predictions; rows (a) and (b) show results for two contrasting realizations of potential future hydraulic head observations. The left column shows, in the lightest color, samples from prior K and S distributions; the center column shows the corresponding 90% CI, also in lightest color. The blue dotted line shows the depth limit, which bisects the prior CI for head, illustrating uncertainty in whether the depletion depth of 287 m.a.s.l. will be reached over 30 years. Each year, a new potential observation is added, shown in black stars in the center column. A corresponding updated CI for head is added in the center column and updated posterior samples from K and S added in the left column; progressively darker colors are used in each time period. The right panel column shows corresponding updated 90% CIs for water shortages assuming no desalination capacity is added.

This result shows the high value of information in reducing predictive uncertainty both in the physical groundwater system and against key planning metrics. The top realization (a) shows a relatively slow drawdown path in which the depth limit is never reached. By year 10, the drawdown CI has been reduced by half and the shortage 50% CI has been reduced by a third with median expected shortages reaching zero. Between years 10 and 20, the CIs continue to narrow but at a much slower rate, illustrating diminishing marginal returns over time to new information as the uncertainty is reduced. Row (b) shows a more rapid depletion rate of the aquifer in which the depth limit is reached in year 17. We observe a similar narrowing of the head confidence interval, but shifted downward reflecting the more rapid rate. While the median expected water shortages stay relatively constant, the uncertainty around the median decreases over time. After year 17, we have complete certainty in total water shortages, having now observed the time at which the water supply ran out. Note that this plot shows two possible sets of observations of hydraulic head and their implications for learning. Across many tested time series of simulated observations, we observe a similar pattern of narrowing confidence intervals with large but diminishing value of information in reducing both predictive uncertainty in head and in water shortages.

3.2. SDP

The SDP develops optimal policies for when to add desalination capacity in the flexible approach, taking into account all the possible future observations of drawdown and associated learning. Figure 4 illustrates these policies as a drawdown threshold. Beyond this threshold, the optimal policy is to add desalination capacity if none has already been added. The drawdown threshold is monotonically decreasing in time; it approaches the depth limit at the end of the planning horizon. This pattern arises from the learning process described in the previous section. If an early observation in year three, for example, shows a hydraulic head of 300 m, we infer that we must have relatively low values for S and/or K and will likely continue on a rapid drawdown path. Therefore, while the head is still 13 m from the depth limit, there is a high probability that the hydraulic head will reach the limit in the next two years. This necessitates a decision today to add capacity that will become available in two years in order to prevent shortages.

3.3. Engineering options analysis

Finally, we use the transition probabilities and the optimal policy results from the SDP to simulate 1000 time series for hydraulic head and the capacity expansion decisions, respectively. These simulated time series are used to assess the cost and reliability performance of the flexible desalination strategy and compare it to static planning alternatives.

Figure 5 shows the distribution of capacity expansion decisions across the 1000 simulations. As indicated by the black bar at the right, desalination

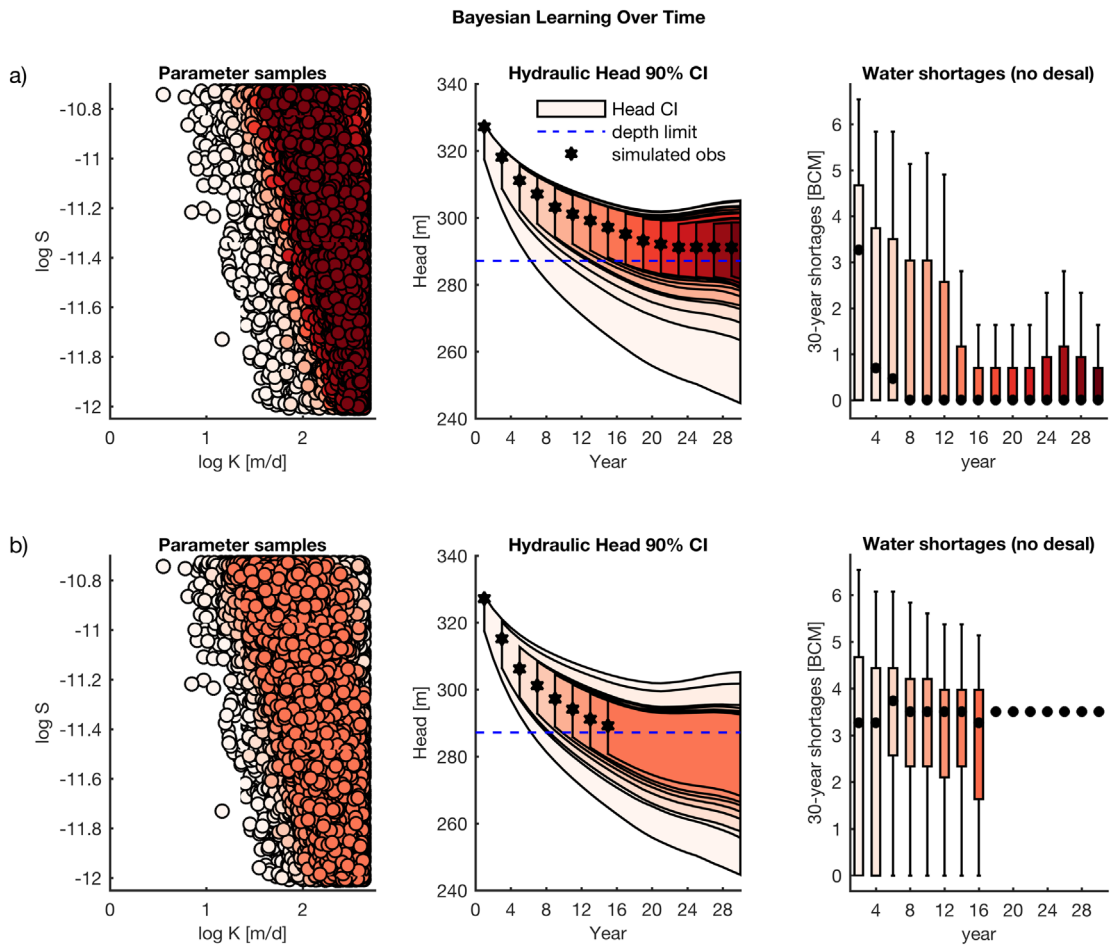

Figure 3. Two realizations (a) slow drawdown, (b) fast drawdown) of sample hydraulic head time series are used to update the parameter distribution (left) and therefore the distribution for projected head (center) and water shortages (right). The darker red colors highlighting a subset of samples in the prior parameter space indicate the ability of the simulated observations to narrow in on a smaller range of realizations of *K* and *S* that could have led to those observations. These updated parameter samples are used in turn to update the predictive uncertainty in hydraulic head which in turn updates uncertainty about total water shortages over the fixed 30 year planning period, assuming no additional supply is added. The large reduction in the confidence interval indicates high value of information both in terms of the physical groundwater system and a key planning metric. However, the value of information faces diminishing returns with additional observations.

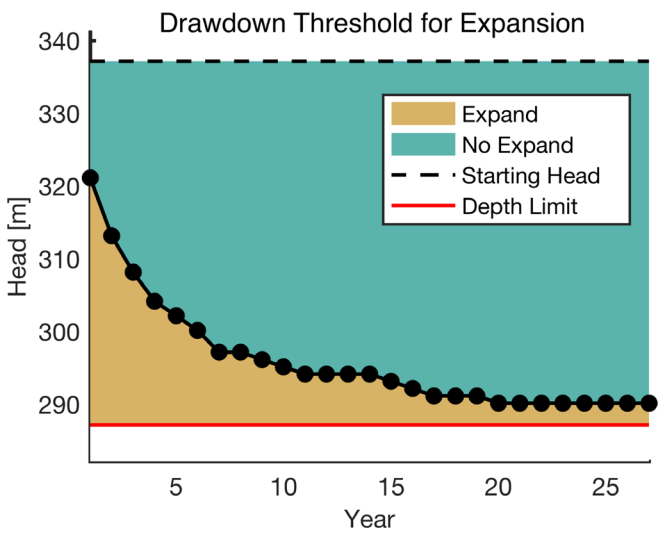

Figure 4. The SDP results provide a hydraulic head threshold beyond which expanding desalination capacity is optimal. The threshold is above the depth limit so that desalination capacity can come online after two years without incurring shortage damages in the interim. This threshold approaches the depth limit as time increases, reflecting that a particular head observation in later time periods reflects a slower drawdown rate than the same observation made in an earlier time period would have.

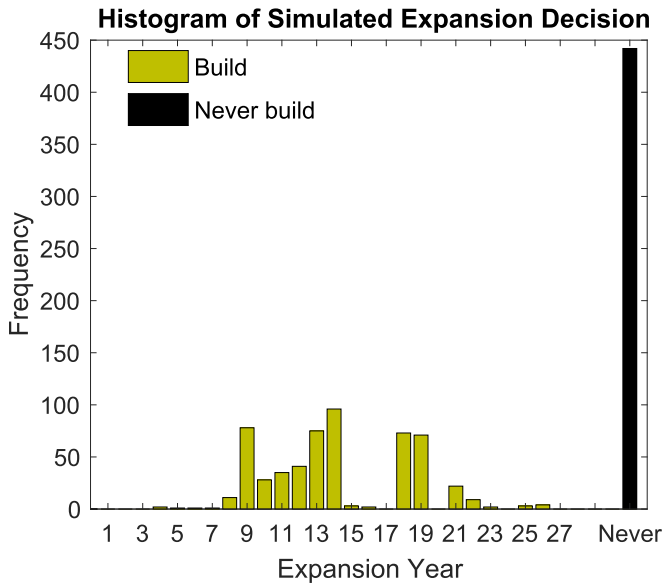

Figure 5. Histogram showing whether and when desalination capacity is added across 1000 forward simulations. The desalination plant is added in under half of simulations. When desalination capacity is added, the timing of that decision variables considerably. This variation is driven primarily by differences in the parameter realizations of K and S across simulations. However, different rates of learning and the finite-horizon formulation of the SDP also contribute to the pattern of time variability.

capacity is never added in 44% of simulations, indicating slow drawdown rates. However, in 56% of simulations, desalination capacity is added, and the time at which it is added varies considerably. Sometimes, as early year 8, a decision is made to bring new capacity online, indicating a very rapid drawdown rate. There is a gap in years 15–17 in which few expansion decisions are made. This corresponds to years where the amount of uncertainty reduction in hydraulic head prediction is limited because the range of annual drawdown across different groundwater model realizations is more similar. Differentiation across groundwater model runs increases again after year 17. Finally, the frequency of expansion tapers off around year 21. This reflects a known limitation of finite-horizon SDP models; they discourage investment late in the planning period when in reality those investments would bring value in the years after the planning horizon ends.

Next, in figures 6(a) and (b) for a zoomed-in view we compare the performance of this flexible strategy (orange) across 1000 simulations to the two static alternatives: one in which the desalination plant is built at the start of the planning period ('build', purple), and one in which the desalination plant is never built ('no-build', green). We present cumulative distribution functions of the total cost including shortage damages, C, over the 30 year planning period. No-build incurs only pumping costs in about 50% of simulations, shown where $0 < F(x) < 0.5$. However, it incurs high damages due to shortages in more than half of simulations. The build alternative is over B$50 more expensive than the no-build alternative in the 50% of simulations when shortages are not incurred, reflecting substantial over-build risk. Modest cost increases in the build alternative, shown where $0.5 < F(x) < 1$, reflect increasing pumping costs and the presence of desalination operating costs.

The flexible alternative mitigates both the over-build risk faced by the build alternative and the reliability risk faced by the no-build alternative. The flexible alternative is far left of no-build where $0.5 < F(x) < 1$, showing that it eliminates nearly all the shortage damages. The flexible alternative is very similar in cost to the build alternative where $0.5 < F(x) < 1$, except small deviations to the right indicating higher overall marginal costs when the plant is built later. The flexible alternative incurs shortages in <1% of simulations. The flexible alternative overlaps the static no-build option in about 40% of simulations where $0 < F(x) < 0.4$, indicating its ability to prevent over-building. In 10% of simulations where $0.4 < F(x) < 0.5$, the flexible alternative does over build. However, the advantages of the static alternatives are limited, given the ability of the flexible alternative to mitigate the worst downsides of both static options. These results are broken out into capital, operating, and shortage costs in SI figure 5.

The results in figures 6(a), (b) assume no discounting. While investment decisions are typically made under discounted cash flow assumptions, this choice enables us to highlight the value of flexibility even in the absence of discounting, which incentivizes the delay of capital investments. Figures 6(a), (b) results also assume a shortage cost of \$20 m^{-3}, based on World Bank estimates of water productivity in Saudi Arabia (The World Bank 2010). Figure 6 also evaluates a discount rate of 5% (c), (d) and shortage costs of \$5 m^{-3} (e), (f) and \$50 m^{-3} (g), (h). These results show that while the absolute cost of each alternative

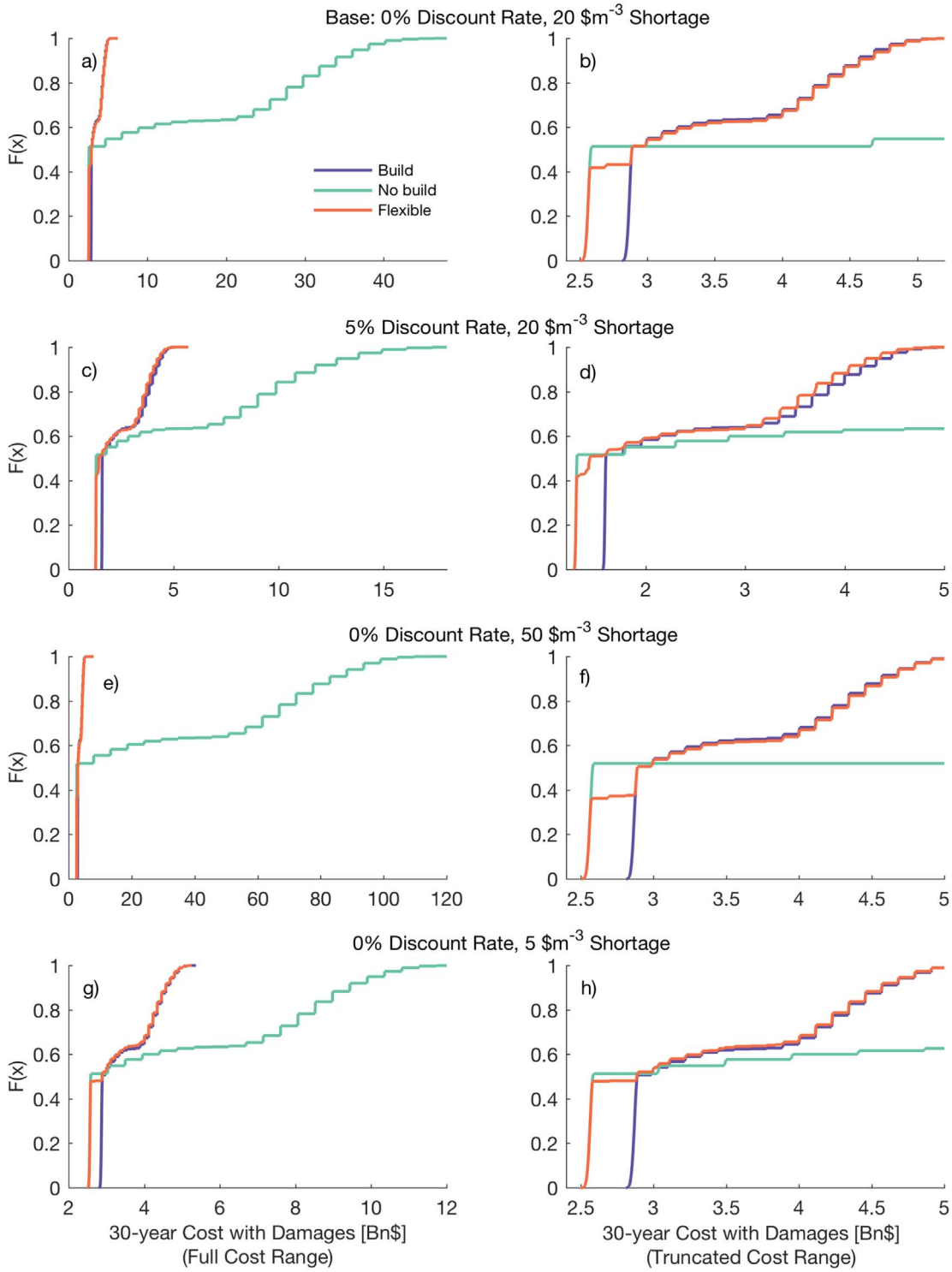

Figure 6. CDF of total cost by infrastructure alternative under varied planning assumptions. Costs include capital and operating cost of desalination infrastructure, groundwater pumping costs, and damages for water shortages. Top row: base case; lower rows: sensitivity analysis. Left column: full cost range shown; Right column: horizontal axis truncated to zoom on key tradeoffs.

varies with planning assumptions, the high value of flexibility is robust across assumptions. Across all three assumptions, the flexible alternative outperforms the other two on expected value, 90th percentile costs, and 10th percentile costs, highlighting again that there is little advantage to either of the static alternatives.

4. Discussion

This paper develops a new framework to evaluate Bayesian learning and flexible planning as strategies to mitigate groundwater resource uncertainty in water supply infrastructure planning. It contributes to the adaptive planning literature by integrating groundwater resource uncertainty with adaptive

infrastructure planning and by extending Bayesian methods for non-stationary SDP to embed a hydrological model.

In our proof-of-concept application, the high value and limited downside of flexible infrastructure planning was robust to variations in the cost of water shortages, the value society places on water reliability, and the social discount rate. This is a striking result that diverges from other studies of flexible infrastructure, where meaningful tradeoffs (e.g. in expected performance versus downside risk) between flexible and static options often require planners to choose based on their risk preferences (de Neufville and Scholtes 2011). This is a unique challenge for infrastructure in particular, rather than adaptive management broadly, due to the high fixed costs and economies of scale inherent in many infrastructure projects. For example, in assessing the potential for a flexible pumping station design to address uncertain flood risk (de Neufville *et al* 2019) found that a flexible approach improved the expected performance but added substantial risk of damages. Fletcher *et al* (2019) showed that a flexible dam design was only favorable with high water shortage costs and/or discounting due to the large economies of scale inherent in dam development.

Here, the robust result arises for three key reasons. First, water table decline happens slowly, allowing the 2 year timeline for the adaptive response to be effective in maintaining reliability; this is in contrast to the sudden nature of flood risk. Second, the additional head observations consistently reduced the uncertainty over time, giving a clearer indication of whether new supply is needed; in Fletcher *et al* (2019) this was not always the case to due the high stochasticity of the climate system and limitation of climate model projections. Third, because the flexibility assessed here is in the timing of infrastructure rather than design, driven by the uncertainty in timing of aquifer decline, economies of scale are not reduced. This case, therefore, helps build theory on the conditions under which adaptive infrastructure is valuable, and suggests further exploration is needed of the impact of stochastic variability, common across many environmental problems, on flexible infrastructure planning. Unlike economies of scale and discounting, stochastic variability has not been explored in-depth in the flexible design literature.

We note that, while the flexible alternative excels from the perspective of infrastructure costs and reliability, adaptive infrastructure planning can pose additional monetary costs not captured here and also requires a high degree of institutional capacity (Stakhiv 2011). Indeed, adaptive management has been shown to be effective only when managers have the resources required for successful implementation (Tompkins and Adger 2004, Rist *et al* 2013). Given that some government agencies are promoting adaptive management as a tool for climate change preparedness (Huntjens *et al* 2011, US Environmental Protection Agency 2012), this underlines the need for approaches to weigh the tradeoffs between adaptive and static infrastructure approaches.

Our proof-of-concept uses a simple groundwater model and planning formulation that allow us to demonstrate the new method with clarity. This formulation has limitations that can be addressed in future applications. The groundwater model does not capture spatial heterogeneity or model uncertainty. The estimated K and S should therefore be interpreted as effective parameters that take on all the uncertainty between observations and predictions. Spatial heterogeneity in aquifer parameters could be included through a zonal or pilot-points approach in which K and S become multivariate vectors that are updated simultaneously in each Bayesian update. The SDP state space would stay the same, but differences in the rate of learning across the parameters zones may impact the head predictions and therefore SDP transition probabilities. Additionally, we use a single grid cell at the center of Riyadh and the cone of depression as a proxy for hydraulic head; results are therefore conservative in that they measure when any pumping in the aquifer becomes infeasible. Future work could include multiple wells by expanding the SDP hydraulic head variable to be a vector of correlated heads at multiple wells. The Bayesian analysis would then use multiple observations (one at each well) in each time period to update the joint posterior of head at all wells.

We have also assumed fixed demand/withdrawals to demonstrate the impact of groundwater resource uncertainty in isolation. Recognizing that changes in demand can have greater impacts than supply (Herman *et al* 2015, Warziniack and Brown 2019), future work could address demand uncertainty by including demand as another variable in the SDP state space. Observations of demand would be taken at each time period and used to update demand forecasts in combination with a model of demand growth; therefore, the planner would learn about demand growth uncertainty over time as well. Deterministic growth rates or seasonality could be included simply by implementing a different fixed assumption about withdrawals over time.

Additional decision variables could be added to the action space including new groundwater development, wastewater reuse, and demand reduction. More active approaches to data collection could be tested; for example, as an alternative to passively collecting new head observations over time, we could include a decision variable to install new monitoring wells to collect information immediately. Similarly, incremental upgrades to existing pumping infrastructure that increase the depth limit could be evaluated as an alternative flexible strategy. The depth limit concept could also be translated to sustainable yields in unconfined aquifers. Evaluating these more varied alternatives would benefit from consideration of additional

planning objectives, such as energy intensity or distributional impacts across end users. We note that these extensions will have to investigate the assumption of path independence, which here is valid due to the monotonically decreasing head in the aquifer and constant withdrawals, and adjust the state space definition if necessary. More broadly, the methodological approach could be adapted to address other civil infrastructure domains such as transportation or energy that are impacted by uncertainty. Exploring such varied future applications can build theory around the drivers of and limits to adaptive infrastructure as a reliable, efficient, and equitable approach for addressing uncertainty.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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