Learning and Flexibility for Water Supply Infrastructure Planning under Diverse Uncertainties

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Abstract

Water supply infrastructure planning faces many uncertainties. Uncertainty in short-term in rainfall and runoff, groundwater storage, and long-term climate change impacts water supply forecasts. Population and economic growth drive urban water demand growth at rapid but uncertain rates. Overbuilding infrastructure can lead to expensive stranded assets and unnecessary environmental impacts, while under building can cause reliability outages with impacts on the economy, ecosystems, and human health. This dissertation assesses the potential for Bayesian learning about uncertainty to enable flexible, adaptive approaches in which infrastructure can be changed over time to reduce cost risk while achieving reliability targets. It develops a novel planning framework that: 1) classifies uncertainties and applies appropriate, differentiated uncertainty analysis tools, 2) applies Bayesian inference to physical models of hydrology and climate to develop dynamic uncertainty estimates, and 3) uses stochastic dynamic programming and engineering options analysis to assess the value of flexibility in mitigating cost and reliability risk. This framework is applied to three applications. Chapter 3 evaluates the potential for modular desalination design to manage multiple, diverse uncertainties — streamflow, demand growth, and the cost of water shortages — in Melbourne, Australia. Chapter 4 addresses uncertainty in groundwater resources in desalination planning in Riyadh, Saudi Arabia, and Chapter 5 addresses model uncertainty in climate change projections in a dam design problem in Mombasa, Kenya. Across all three applications, we find value in flexible infrastructure planning with a 9–28% reduction in expected cost. However, the performance of flexible approaches compared to traditional robust approaches varies considerably and is influenced by technology choice, economies of scale, discounting, the presence of irreducible stochastic variability, and the value society places on water reliability.

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Glossary

ANN	artificial neural network.
ARMA	auto-regressive moving average.
BMA	Bayesian model averaging.
°C	degrees Celsius.
CDF	cumulative density function.
CI	confidence interval.
CMIP5	coupled model intercomparison project, phase 5.
CRU	Climate Research Unit.
DAPP	dynamic adaptive policy pathways.
ENSO	El Niño–Southern Oscillation.
EOA	engineering options analysis.
GCM	general circulation model.
IPCC	Intergovernmental Panel on Climate Change.
K	hydraulic conductivity.
kL	kiloliters.
km	kilometer.

kNN	k nearest neighbors.
m	meter.
m.a.s.l.	meters above sea level.
m.b.l.s.	meters below land surface.
M$	million US dollars.
m^3/d	cubic meters per day.
MAR	mean annual runoff.
MCM	million cubic meters.
MCM/d	million cubic meters per day.
MCMC	Markov chain Monte Carlo.
mm	millimeters.
MORDM	many-objective robust decision making.
P	precipitation.
RCP	representative concentration pathway.
RDM	robust decision making.
RO	reverse osmosis.
ROF	risk of failure.
S	storativity.
SDP	stochastic dynamic programming.
T	temperature.
USGS	United States Geological Survey.

Chapter 1

Introduction

1.1 Motivation and background

Australia faced its driest decade in recorded history from 1997 to 2009. Known as the "Millennium Drought," this period had severe impacts on Australia's economy, environment, and citizens. The agriculture sector was especially damaged, with low crop yields forcing small farms out of production and mid-size farms into financial distress [4]. Salinity in the River Murray reached record levels, impacting water supplies for human and livestock consumption and damaging ecosystems [38]. The city of Melbourne was among the hardest hit. The utility Melbourne Water and the Victorian government implemented a host of measures to increase supply and reduce demand in the city, including increased water tariffs, wastewater recycling, water use restrictions, and rainwater harvesting installations [97]. Despite these measures, reservoir levels in 2007 reached below 30%, or less than one year's worth of supply [105]. This prompted Melbourne Water to contract the Wonthaggi desalination plant, a 150 million cubic meters (MCM) per year reverse osmosis (RO) plant with a capital cost of $5 billion [58]. However, the drought ended in 2009, and intense rains filled the reservoir system before the Wonthaggi plant was completed in 2012 [97]. This left the $5 billion asset completely idle for the next five years, sparking substantial public controversy. The Wonthaggi plant has been called "the most criticized desalination investment to have occurred in the last decade certainly in Australia, if not the world" [126].

However, the situation facing water planners in 2007 was dire. It is impossible to know how long a drought will last, and the El Niño–Southern Oscillation (ENSO) cycle commonly causes prolonged dry periods in the region. Similar cases of large desalination investments laying idle for years after completion have occurred in London [13], California [64], and Spain [22]. However, there are also plentiful examples of cities relying on desalination investments to weather droughts — or wishing they had made those investments earlier. In Perth, which was also severely impacted by the Millennium Drought, planners invested in a smaller (45 MCM/y) RO plant that was completed in 2006 at the peak of the drought and heralded as a success [126]. Perspectives are shifting in Melbourne, where a new dry period led Melbourne Water to use the Wonthaggi plant for the first time last year [1]. A long-mothballed desalination plant from the 1990s in Santa Barbara, California was retrofitted during the recent drought in 2015 [64]. Finally, as ongoing drought in Cape Town, South Africa fuels debate on whether 2018 will bring "Day Zero" when water supplies in the city completely run out, water managers are scrambling to bring desalination capacity online quickly [27]. Researchers at the University of Melbourne predict that the controversial Wonthaggi plant could save Melbourne from a "Day Zero" of its own [155].

These examples highlight the challenge of planning water supply infrastructure for an uncertain future. Water planners must ensure reliable, high-quality access to freshwater for domestic, agricultural, and industrial end-users while meeting financial and institutional constraints and preserving the sustainability of natural resources. Over-investment in infrastructure can lead to stranded assets worth hundreds of millions or billions of dollars and unnecessary environmental impacts. Under-investment can lead to supply restrictions or outages with consequences for the economy, environment, and human health. This challenge is exacerbated in many regions of the world by the confluence of growing populations and economies with a changing climate.

Water planners rely on forecasts of supply and demand that are inherently uncertain. Variability in the hydrological cycle at varying scales — daily, monthly, annual, decadal — leads to uncertainty in surface water availability. Groundwater storage is also often affected by hydrological variability, often with greater lag times than surface water. Further, the substantial heterogeneity of groundwater aquifers in combination with the difficulty in measuring groundwater flow leads to additional uncertainty in groundwater resources. Over long time scales, climate change is expected to alter the hydrological cycle, rendering inappropriate the use of stationary stochastic processes to characterize uncertainty — and making water resources planning and management all the more difficult. [108]

Social and economic factors also present uncertainty. In addition to uncertainty in how the climate system will respond to greenhouse gas emissions, political and institutional decision-making at regional, national, and international scales drives uncertainty in the magnitude and timing of greenhouse gas emissions. However, in many regions of the world, population growth, economic growth, and urbanization are expected to have a greater impact on water scarcity than climate change [164]. Finally, uncertainty is compounded by ambiguity [20], also known as evaluative complexity [43], or differing preference across stakeholders about the relative importance of water reliability, ecological preservation, cost, and sustainable resource use for future generations.

Water managers have a number of tools for managing uncertainty and variability in water resource systems. Demand policies, incentives, and restrictions can reduce end-user demand during times of low supply. Existing infrastructure, such as reservoir systems, pipelines, desalination plants, and wastewater treatment for reuse can be managed and operated to smooth variability in supply and hedge against future uncertainty. Coordination with neighboring water suppliers can be used to import additional supplies when reserves are low. New infrastructure can be added to address immediate drought conditions or meet long-term needs. However, new water infrastructure faces additional challenges from uncertainty. New infrastructure requires large capital investments often on the order of hundreds of millions or billions of dollars. These investments have long lifetimes: desalination plants and dams have lifetimes on the order of 30 years and 100 years respectively. Infrastructure projects are typically fixed, static investments that are difficult to change once built. However, they interact with complex and evolving human and natural systems over their lifetimes [35]. The confluence of these factors heightens the risk that water supply infrastructure investments will fail to meet performance goals in the face of uncertainty — and necessitates the development of new approaches to reduce and manage risk.

1.2 Recent methods for water supply planning under uncertainty

Historically, uncertainty in water infrastructure planning has been managed by adding a safety factor to a single best forecast [149]. Dams were sized using historical streamflow data, without accounting for the possibility that the future could bring more or different variability than the past. Since the 1980s, risk-based metrics such as reliability and vulnerability have been promoted for managing water supply systems [67]. Scenario-based planning, in which planners develop a few alternate visions of the future and choose a set of strategies that address the potential for each scenario to occur, is now widely used in water infrastructure planning. Climate change has also driven the use of adaptive management, in which planners prepare to adapt as uncertainties unfold over time, over the past two decades [115].

In the past 15 years, more sophisticated approaches for water supply planning under uncertainty have developed. Three critical insights in this literature include: 1) explicit recognition of the limitations of forecasts and therefore the need to develop strategies that are relatively insensitive to forecasts; 2) the need for bottom-up vulnerability analysis, in which the conditions that lead to system failure are identified and evaluated, and 3) the potential for flexible or adaptive approaches to manage uncertainty.

The first insight is addressed by robust decision making (RDM), developed by Lempert et al. (2006) [93] with early applications in water planning [60, 92]. RDM uses a scenario-based approach to identify robust strategies that meet performance criteria across many possible futures. This approach is motivated by the concept of "deep" uncertainty in which there is so much uncertainty that probabilities cannot or should not be assigned to the various potential outcomes [166]. This is distinct from "recognized ignorance" or Knightian uncertainty [88], in which not even all the possible outcomes can be identified [166]. Groves and Lempert (2007) argue that climate change is a deep uncertainty and therefore that traditional probabilistic decision-analytic methods are inappropriate [60]. Many-objective robust decision making (MORDM) has extended RDM to include many performance criteria relevant for water planners and uses multi-objective evolutionary algorithms to efficiently identify Pareto optimal strategies in large scale systems [86].

Second, bottom-up vulnerability analysis has played an important role in water supply planning under uncertainty. In the info-gap approach developed by Ben-Haim (2001), the analysis develops increasingly large multidimensional uncertainty sets and identifies the solutions that meet threshold performance criteria for each uncertainty set [14]. This allows planners to identify uncertainty thresholds beyond which a certain planning strategy fails. More recently, decision scaling, developed to address climate change uncertainty specifically, links bottom-up vulnerability analysis with climate change projections [19]. Decision and performance thresholds are identified first and then combined with ensembles of general circulation model (GCM) projections, allowing planners to both make use of GCM projections and also understand their limitations.

Finally, a number of approaches have built on early calls for adaptive management as a strategy to manage climate change uncertainty. Adaptive management can enable reliability at reduced cost by developing plans to ensure short-term water needs are met without investing in permanent solutions before the long-term future is well understood. Recent methods such as adaptation tipping points [62] and dynamic adaptive policy pathways (DAPP) [61, 89] enable policymakers to identify tipping points or thresholds beyond which new polices will be needed. Identifying these thresholds in advance — and the policies to be implemented if they are reached — enables a planned adaptation approach in which adaptive policies are fully developed and can be nimbly executed when needed, reducing short-term transition risks [102]. Defining "dynamic robustness" as flexibility enabling a plan to change in response to changing conditions over time, Walker et al. (2013) raises the limitations of RDM in developing dynamic robust solutions and highlights the value of DAPP in achieving dynamic robustness [165].

A different approach to adaptive or flexible planning is used in engineering options analysis (EOA). EOA is an approach related to real options analysis, which applies financial valuation of options to capital investment decisions [33]. EOA focuses on assessing engineering options, or flexibility in engineering design and planning, using related methods. Flexible options can be identified using screening models, stochastic optimization, or simple decision rules [11]. In contrast to real options analysis, EOA focuses on exploring and weighing the various benefits and costs using uncertainty analysis rather than developing precise estimates of the value of flexible options [34]. Therefore, while it uses probabilistic approaches to assess uncertainty, the interpretation of the probabilistic results can be adapted to address deep uncertainties. This method has been applied to infrastructure domains ranging from satellite systems [35] to liquefied natural gas production [23]. In water resources, early applications have applied EOA to infrastructure planning problems in desalination [51], dams [80], and hydropower [153].

Research questions

This thesis addresses three main gaps in the above literature and develops a novel framework for planning under uncertainty to address them. First, while the recent methods addressing deep uncertainty, such as RDM, have played an important role in acknowledging the limitations of probabilistic forecasts and developing planning approaches that are relatively insensitive to these limitations, many of the common uncertainties that impact water supply infrastructure planning can be treated probabilistically. RDM typically addresses all the uncertainties using scenario analysis. However, uncertainties can be addressed in the same analysis using different methods. Previous work in dimensions of uncertainty — which differentiate deep uncertainty from statistical uncertainty, for example — can serve as a basis to classify uncertainties and map them to appropriate analysis tools.

Second, another limitation in existing approaches is a focus on static rather than dynamic approaches to characterizing climate and hydrological uncertainty in infrastructure planning. The scenario approach in RDM, for example, assesses the performance of a planning alternative within a single scenario, assuming the conditions of that scenario extend over the entire planning horizon; the uncertainty is addressed by comparing many different scenarios. This approach does not allow for updated assessment of uncertainty within a single scenario to drive adaptive strategies in which infrastructure plans or designs can be changed. Other approaches described above, such as DAPP and EOA, do take a dynamic approach to uncertainty that enables flexible or adaptive approaches. However, DAPP is focused on policy rather than infrastructure planning; it does not provide a framework to develop and assess the performance of flexible infrastructure planning and design, which face additional challenges due to the large capital investments required and long lifetimes. EOA does provide the necessary framework to evaluate flexible infrastructure planning and performance. However, it does not currently integrate models of the natural environment to characterize hydrological or climate uncertainty. The research gap, therefore, lays in developing a planning approach that integrates all three characteristics: a dynamic approach to uncertainty, infrastructure planning and performance, and appropriate physical models.

Finally, existing approaches do not provide a framework for evaluating the value of flexibility in managing hydrological uncertainty. While some recent approaches to water supply infrastructure sequencing include flexibility as an objective in a multi-criteria decision problem [12], these approaches do not provide a basis for assessing whether flexibility is a worthwhile objective. Flexibility is a life-cycle system property of an engineering system that can be useful in achieving performance goals, not a performance metric itself [35]. Flexibility has a cost: either physical infrastructure investments that must be made in order to enable flexible options in the future and/or institutional preparations to enable timely and efficient transitions once a decision is made to exercise an option. Comparing these costs to the potential benefits of flexibility is necessary in order to determine whether flexible approaches are worth implementing.

This leads to the three overarching research questions addressed in this dissertation:

1. How do multiple, diverse uncertainties impact water supply infrastructure planning?
2. How can Bayesian updating of hydrological uncertainty be used to develop dynamic uncertainty estimates for flexible planning?
3. How valuable is flexibility in managing diverse uncertainties?

This dissertation addresses these questions through the development of a new framework for water supply infrastructure planning under uncertainty and its application to three contrasting planning problems. The planning framework addresses question 1) by using existing dimensions of uncertainty as well as a new dimension in order to classify uncertainties and connect them to appropriate uncertainty analysis tools so that multiple, diverse uncertainties can be addressed in a differentiated approach in a single analysis. Question 2) is addressed using Bayesian inference applied to climate and hydrological models to develop dynamic assessments of uncertainty, which are embedded in a multi-stage stochastic planning approach to develop policies for exercising flexible infrastructure options. Statistical surrogate models are used as needed to enable computational tractability. Finally, the planning framework draws on engineering options analysis to assess the value of flexibility in mitigating hydrological uncertainty and address question 3).

The remainder of this dissertation is organized as follows. Chapter 2 introduces the framework for flexible water supply infrastructure planning under multiple uncertainties. Chapter 3 applies the framework to a retrospective desalination planning problem based on the Millennium Drought in Melbourne, Australia. The focus of this application is in addressing question 1) by integrating three different uncertainties with different classifications into a single analysis. Chapters 4 and 5, in contrast, focus on addressing question 2) by developing approaches for applying Bayesian inference to hydrological and climate models in order to characterize the transition probabilities in a stochastic dynamic program. Chapter 4 addresses parameter uncertainty in groundwater availability in a desalination planning problem in Riyadh, Saudi Arabia, and Chapter 5 addresses model uncertainty in climate

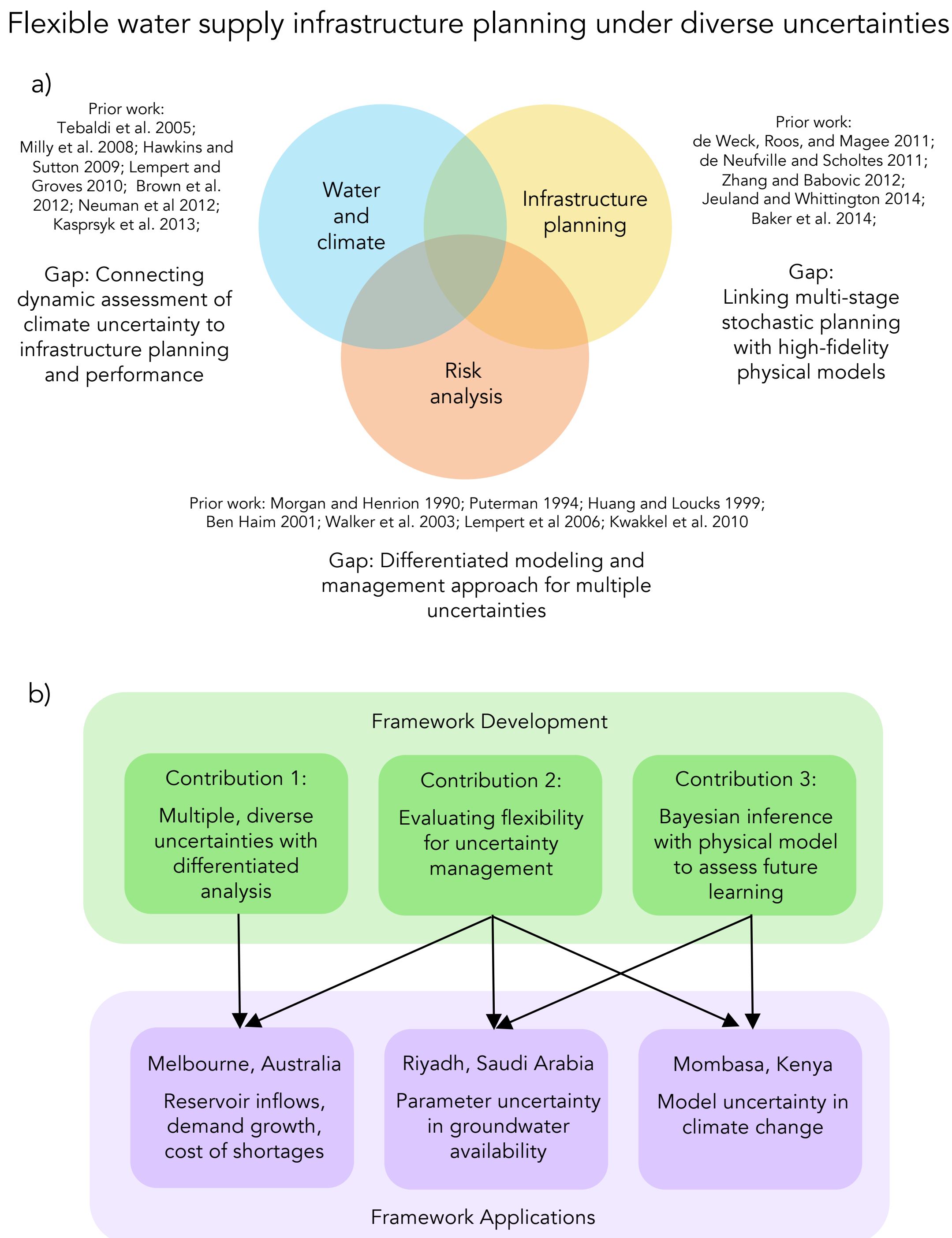

Figure 1-1: a) Key literature areas with prior work and gaps addressed in this dissertation and b) novel planning framework with key contributions (top) and applications to demonstrate those contributions (bottom).

change projections in a dam design problem in Mombasa, Kenya. All three applications address question 3) by assessing the value of flexible planning and design in comparison to static, robust approaches. Finally, Chapter 6 concludes with discussion of insights across the individual applications and potential for future development of the planning framework. Chapters 3, 4, and 5 are presented as stand-alone papers; while there is some overlap in literature review and methods across the chapters, this approach allows them to be read and used in isolation without reviewing the dissertation as a whole.

Chapter 2

Water supply infrastructure planning under multiple, diverse uncertainties: A differentiated approach

The previous chapter provided an introduction to the uncertainties that commonly impact water supply infrastructure systems and the tools available to manage those uncertainties in planning decisions. Research over the past 15 years has made important advances in 1) developing approaches that enable infrastructure planning strategies that are relatively insensitive to long-term uncertainty and 2) emphasizing the necessity of bottom-up vulnerability assessments as a complement to top-down planning approaches. Both of these advancements are important in addressing uncertainties that are poorly characterized or otherwise difficult to predict. However, they have also led to a tendency to address all uncertainties in a problem using the same approach. A variety of modeling tools and management strategies exist to address uncertainties; different approaches may be more effective for one specific uncertainty than another.

Here we present a framework for modeling and managing multiple, diverse uncertainties within a single analysis. The goal of this framework is to address three key limitations in current approaches for water supply planning under uncertainty. First, we take a differentiated approach to uncertainty analysis in which different types of uncertainty are addressed with unique, appropriate methods. There are many existing dimensions of uncertainty and uncertainty analysis methods. However, less attention has been paid to matching specific

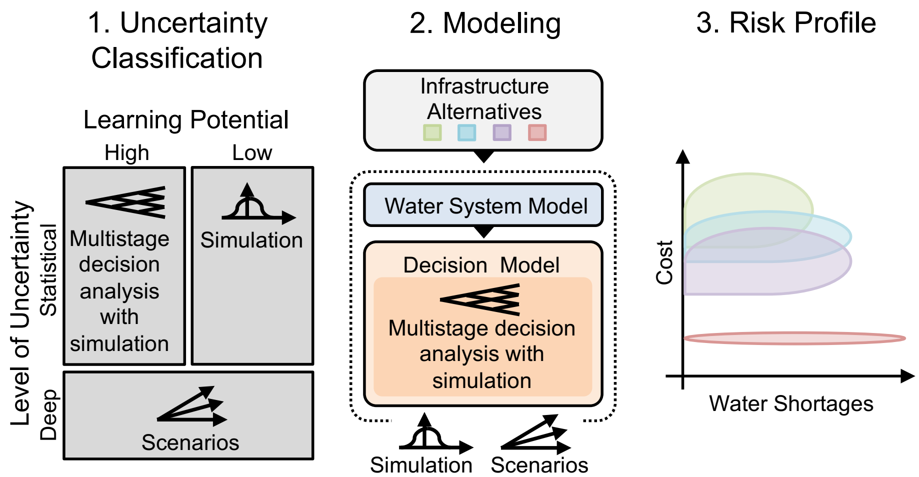

Figure 2-1: Framework for classifying, modeling, and managing multiple diverse uncertainties in water supply infrastructure planning.

types of uncertainty to analysis or management tools. The methods that have developed to address deep uncertainty in water resource system planning, for example, tend to treat all uncertainties in the analysis as deep rather than separating out the deep uncertainties from the statistical ones. Second, when necessary we take a dynamic approach to uncertainty in which probabilistic estimates are updated in a Bayesian manner over time. Our planning model uses hypothetical future observations to update forecasts, allowing us to account for the potential to learn in the future in planning decisions today. Finally, we assess the value of flexibility in water supply infrastructure planning and design; current approaches either do not consider flexibility or include it as a planning objective without knowing whether it will be worthwhile in achieving performance goals.

Our framework for water supply infrastructure planning under multiple uncertainties comprises three main steps, illustrated in Figure 2-1. First, uncertainties are classified according to two dimensions: the level of uncertainty and learning potential. Analysis methods are then chosen based on this classification. Second, a modeling approach is applied in which infrastructure plans or designs are developed and integrated into a water resource system model that comprises a hydrological model of the region of interest and the impact of infrastructure on that system. This model is embedded in a multi-stage stochastic planning model, such as a stochastic dynamic programming (SDP). Finally, the result of this is to develop risk profiles for the different infrastructure alternatives that highlight areas of vulnerability and strength against key performance metrics. These three steps are discussed in more detail below.

2.1 Uncertainty classification and analysis method

The first step in the framework is to 1) classify uncertainties into three categories, and 2) apply a differentiated uncertainty analysis method appropriate for that category.

Uncertainty classification

Existing uncertainty dimensions. A diverse range of uncertainties impact water supply planning decisions. These include: short-term variability in rainfall and runoff, long-term climate change, uncertainty in groundwater availability, population growth and urbanization at uncertain rates, and the value of water during times of scarcity. Each of these uncertainties has unique characteristics and can be classified according to different dimensions. Several existing dimensions of uncertainty are presented in the "uncertainty matrix" developed by Walker et al. (2003) [166], updated by Kwakkel et al. (2010) [90], and illustrated in Figure 2-2. Here we summarize and extend the uncertainty matrix to use in our classification system.

The *level of uncertainty* as coined by Walker et al. (2003) [166] describes the magnitude of uncertainty ranging from determinism to recognized ignorance. These authors develop three levels: statistical uncertainty in which the full range of outcomes is known and probabilities can be reliably placed on these outcomes; scenario uncertainty in which the possible outcomes can be identified but they can not be characterized probabilistically; and recognized ignorance in which the full range of possible outcomes is unknown. This refines a much earlier distinction between risk, which can be defined probabilistically, and Knightian uncertainty, which is immeasurable [88]. Similar distinctions have been drawn more recently, such as Luce and Raiffa (1957) [99] who distinguish between decision making under risk and decision making under uncertainty and Morgan and Henrion (1990) [112] who distinguish between uncertainties that can be described probabilistically and those that cannot. Most recently, Kwakkel et al. (2010) [90] further refine this dimension of uncertainty to improve clear operationalization with four categories.

One of the four categories defined by Kwakkel et al. (2010) is "deep uncertainty", defined as "being able to enumerate multiple alternatives without being able to rank order the alternatives in terms of how likely or plausible they are judged to be" [90]. The concept of deep uncertainty has indeed motivated many of the approaches for decision-making under uncertainty described in the previous chapter such as RDM or decision scaling. However, there is disagreement about how to conceptually define and operationalize this concept. Groves and Lempert (2007) [60] alternatively define deep uncertainty as "the situation where decision makers do not know nor cannot agree upon the system model that relates action to consequences, the prior probabilities on the inputs to the system model(s), or the value function that ranks the desirability of the consequences". Despite definitional disagreements, in practice most researchers have argued that deep uncertainty requires 1) the use of scenario-based or otherwise non-probabilistic approaches to uncertainty and/or 2) bottom-up approaches that focus on identifying areas of vulnerability rather estimating the probability of reaching them [93, 19, 14]. However, a different school of thought used in engineering options analysis uses probabilistic approaches as a means to sample from a wide distribution of possible outcomes; the interpretation of the results is therefore not focused on precise calculations of expected value but rather on highlighting trade-offs between alternatives [34].

The *location of uncertainty* refers to where in the analysis or modeling process the uncertainty occurs including the input data, parameters, model, or interpretation of the results [166]. Uncertainty in input data, for example, recognizes the limitations and inherent error in the way measurements of hydrological processes like evaporation, streamflow, and hydraulic head are made. The distinction between model and parameter uncertainty is increasingly common in practice, with the use of multi-model comparison tools such as Bayesian model averaging (BMA) applied to estimate uncertainty across models [74]. This distinction can, however, be blurry when it is unclear what aspects of the analysis are "parameters" and which are components of the "model". For example, groundwater withdrawals and recharge are typically formulated as boundary conditions in numerical groundwater models, and boundary conditions are typically considered part of the model structure. However, withdrawals and recharge rates are also often treated as parameter uncertainty. In practice, this distinction is becoming less important as methods such as Bayesian hierarchical modeling are increasingly used to integrate parameter uncertainty into estimates of model uncertainty [140]. The context or interpretation of the results can also be viewed as an uncertainty. Some researchers describe this as "ambiguity" [20] or "evaluative complexity" [43]. While the uncertainty matrix addresses it as a location of uncertainty [166], others have suggested it as a

Location		Level			Nature	
		Statistical uncertainty	Scenario uncertainty	Recognised ignorance	Epistemic uncertainty	Variability uncertainty
Context	Natural, technological economic, social and political, representation					
Model	Model structure					
	Technical model					
Inputs	Driving forces					
	System data					
Parameters						
Model Outcomes						

Figure 2-2: Uncertainty matrix reproduced from Walker et al. 2003 [166]

different nature of uncertainty (see next paragraph) in comparison to epistemic or aleatory [20].

The *nature of uncertainty* refers to whether the uncertainty arises from natural stochastic variability or from a lack of information [166]. These two categories are often called aleatory and epistemic uncertainty, respectively. Natural variability arises through some kind of stochastic process: a random variables takes on different values in time or in space. Rainfall is a classical example of natural variability in hydrology. Many parametric processes, such as auto-regressive lag-1 processes or other Markov processes [138], as well as nonparametric processes, for example using re-sampling of historical observations [176] or bootstrapping methods [91], have been proposed as models of the stochastic process governing daily or monthly precipitation. Soil properties such as hydraulic conductivity or porosity exhibit natural variability in space rather than time; random fields are often used to represent this variability [175]. In contrast, epistemic uncertainty arises from a lack of information: there is a single value that we can know in principle but do not because of a lack of information. For example, the population of the city of Melbourne at the start of 2050 will have a single value, but we do not have access to that information and therefore epistemic uncertainty arises.

While the difference between aleatory and epistemic uncertainty has a long history of use, the distinction between them is not always clearly defined and indeed many uncertainties have characteristics of both. For example, rainfall, as described above, clearly exhibits variability due to a stochastic process. However, precipitation in Cambridge, MA on May 1, 2020 will take on a single value, but we do not currently have the information to identify it precisely, only a statistical description of the underlying process. It therefore has properties of epistemic uncertainty as well. This dual interpretation of uncertainty has a long history in water resources. Dettinger and Wilson (1981) [40] present a statistical description of aquifer hydraulic conductivity using a mean and spatial covariance with two interpretations. In the first, the statistical description represents the underlying stochastic process that leads to spatial variability in the aquifer. In the second, it represents an estimation of the true field and the modeler's degree of belief in that estimate. These interpretations reflect the aleatory and epistemic aspects of uncertainty, respectively. Dettinger and Wilson (1981) [40] highlight an important distinction, however: aleatory uncertainty is irreducible while epistemic uncertainty can be reduced. An aquifer's hydraulic conductivity will always have a pattern of spatial variability, while our description of it can be more and more precise. In practice, however, probability theory is widely applied to both types of uncertainty even though the interpretation is quite different.

Our uncertainty classification approach. We classify uncertainties according to two dimensions; the "level" dimension above and a new dimension we call "learning potential". The dimensions of uncertainty can be understood as continua. For example, the level of uncertainty ranges from determinism at one end to recognized ignorance at the other. However, mapping uncertainties to uncertainty analysis methods requires discrete categories as the analysis methods (e.g. scenario analysis or Monte Carlo simulation) are themselves discrete. We therefore split the dimensions into discrete categories with operational definitions to reliably code the uncertainties.

The first dimension we use is the level of uncertainty. We address two discrete categories in this dimension: statistical uncertainties and deep uncertainties. We define statistical uncertainties as those that can be appropriately characterized probabilistically and validated using historical data. We define deep uncertainties as those for which the possible outcomes can be identified but probabilities cannot reliably be placed on them; or those probabilities cannot be validated. Recognized ignorance, in which the outcomes cannot be identified, is not addressed. This classification is important for choosing an uncertainty analysis method because it determines whether it is appropriate to use probabilistic uncertainty methods or not.

The second dimension of uncertainty used for classification is a new dimension herein termed learning potential. It is related to the idea of information or epistemic uncertainty, but it reflects pragmatically whether information uncertainty can be reduced. We define two categories along this dimension: high and low learning potential. Uncertainties with high learning potential are defined as those for which new observations can be collected, either presently or in the future as new observations become available, to reduce or update uncertainty in a way that meaningful impacts forecasts for decision-making. Low learning potential uncertainties are those which cannot be meaningfully updated, either because new information cannot be feasible collected or because the new information does not meaningfully change previous forecasts. This dimension has two advantages over the traditional epistemic vs. aleatory definition. First, it does not suffer from the problem that, as described above, epistemic and aleatory are not mutual exclusive categories and in fact most uncertainties can likely be considered as having elements of both. For this new dimension, there are either opportunities to reduce or update the uncertainty, or not. Second, it is connected to an important choice in how we model uncertainty: whether we assess uncertainty statically or dynamically in which estimates of uncertainty can change over time. The distinction between epistemic and aleatory uncertainty often does not inform a choice of uncertainty analysis tool; probabilistic approaches are widely applied for both.

Together, these dimensions define three categories: deep uncertainties (which includes both high and low learning potential uncertainties), high learning-potential statistical uncertainties, and low learning-potential uncertainties. Common uncertainties impacting water supply infrastructure planning are listed in Table 2.1 along with their classification and analysis tool used.

Table 2.1: Key uncertainties in water supply infrastructure planning with classification, justification, and analysis tool

Uncertainty	**Classification**	**Justification**	**Analysis Tool**
Short-term variability in streamflow	Statistical; low learning potential	Well-characterized by historical data; stationarity assumption appropriate over short time scales	Monte Carlo simulation; applied using stochastic streamflow generation
Population growth rate	Statistical; high learning potential	Well-characterized by existing demographic forecasts; early changes in growth rate highly predictive of future growth	Multi-stage stochastic planning; dynamic uncertainty uses simple conditional growth rate assumptions
Water shortage penalty value	Deep uncertainty	This is an ambiguity, or uncertainty arising from differences in stakeholder perspective	Scenario analysis
Parameter uncertainty in groundwater	Statistical; high learning potential	Characterized probabilistically in previous hydrogeological studies; can be improved substantially with addition head observations	Multi-stage stochastic planning; dynamic uncertainty uses Bayesian inference with a groundwater model to update parameter estimates
Model uncertainty in climate change	Statistical; high learning potential	Validated statistical model exists for climate model uncertainty; Uncertainty changes as observations of long-term trends become available	Multi-stage stochastic planning; dynamic uncertainty uses Bayesian model averaging, updated as new observations are available
Scenario uncertainty in climate change	Deep uncertainty	Greenhouse gas emissions over long-time scales are influenced by global geopolitics	Scenario analysis

Uncertainty analysis methods

Next, we map the three uncertainty categories to uncertainty analysis methods. We apply probabilistic approaches for statistical uncertainties and scenario-based approaches for deep uncertainties. This allows us to take advantage of the full information available for statistical uncertainties without presenting deep uncertainties with over confidence. For deep uncertainties, a variety of scenario-based methods could be used. For example, the Latin-hypercube simulation approach to scenario generation developed in RDM could be applied. In our framework, this approach would only be used for deep uncertainties, in contrast to RDM which applies this approach to all uncertainties. In our applications, we simply repeat the analysis under different input assumptions or scenarios to assess the impact of uncertain assumptions on the risk profiles of different alternatives.

For statistical uncertainties, we apply two different uncertainty analysis approaches for high and low learning potential uncertainties. Low learning potential statistical uncertainties are addressed using Monte Carlo simulation. This takes advantage of available statistical information in a computationally efficient manner.

High learning potential uncertainties, however, require a dynamic approach to uncertainty in which estimates of future uncertainty can be updated over time. Existing methods, for example the risk of failure (ROF) method developed by [123], allow uncertainty estimates to vary as a function of the state of the system but not as a function of time independent of the state of the system. For example, predictions of reliability outages may be higher in time period 5 than in time period 2 because reservoir storage levels are lower in time period 5; this is addressed under the ROF approach. However, the probability of reliability outages in time period 5 could be different than in time period 2 even if the reservoir storage level is the same because the planner's understanding of the hydrological system has changed; this is not addressed in the ROF approach. This is an important limitation. We therefore develop a dynamic approach to characterizing uncertainty so that it can be updated to reflect new or improved information.

We use Bayesian inference applied to a physical hydrological or climate model to characterize dynamic uncertainty estimates and embed these in a multi-stage stochastic dynamic program. SDP is a multi-stage stochastic optimization approach used to develop optimal policies as a function of the system state and time period [128]. It takes into account future uncertainty using transition probabilities $p(S_{t+1}|S_t)$ which describe the 1-step transition from a state in time period t to a new state in $t+1$. Non-stationary transition probabilities, in which $p(S_{t+1}|S_t = o)$ does not necessarily equal $p(S_{y+1}|S_y = o)\ \forall\ t \neq y$, are used to reflect learning about the system over time. The optimal policies are derived by solving the Bellman equation, shown in Equation 2.1, using recursion.

$$V(s,t) = \underset{a\in A}{\operatorname{argmin}}\ C\big(s(t), a(t), t\big)\ +\ \gamma \sum_{s\in S} p\big(s(t+1)\,|\,s(t), a(t)\big)\ *\ V\big(t+1, s(t+1)\big) \quad (2.1)$$

where V is the optimal policy; s is the state of the system from the state space S; t is the time period or stage; a is an action from a set of possible actions A; C is the single-period cost as a function of the current state, action, and time; γ is the discount rate; and $p\big(s(t{+}1)\,|\,s(t), a(t)\big)$ are the transition probabilities as a function of the current state, action, and time.

The challenge in addressing hydrological uncertainties using SDP lies in using high-fidelity physical models to characterize the transition probabilities. An overview of our approach is shown in Figure 2-3. First, the state space S is defined and discretized to represent the uncertain hydrological variable(s) of interest. The groundwater application in Chapter 4 uses hydraulic head in a groundwater aquifer as the uncertain state variable; the climate change application in Chapter 5 uses decadal mean temperature and precipitation as the uncertain state variables. A planning horizon is also defined and discretized into time steps; the length is chosen to reflect the approximate lifetime of the relevant infrastructure.

Second, a physical model that forecasts the uncertain state variable is developed or selected. Chapter 4 uses the groundwater model MODFLOW, and Chapter 5 uses an ensemble of GCM projections. Optionally, a statistical surrogate model can be developed based on the physical model to enable or improve computational tractability. In Chapter 4, an artificial neural network is trained on MODFLOW output to serve as a surrogate. The physical model is used to develop a prior distribution $p(S_t)$. This is operationalized differently depending on the location of uncertainty (e.g. parameter vs. model uncertainty: see description in Section 2.1). For parameter uncertainty, Monte Carlo simulation on the uncertainty parameter can be applied; this is done in Chapter 4 for parameter uncertainty in hydraulic conductivity and storativity. Bayesian model averaging [74] can be applied to address model uncertainty;

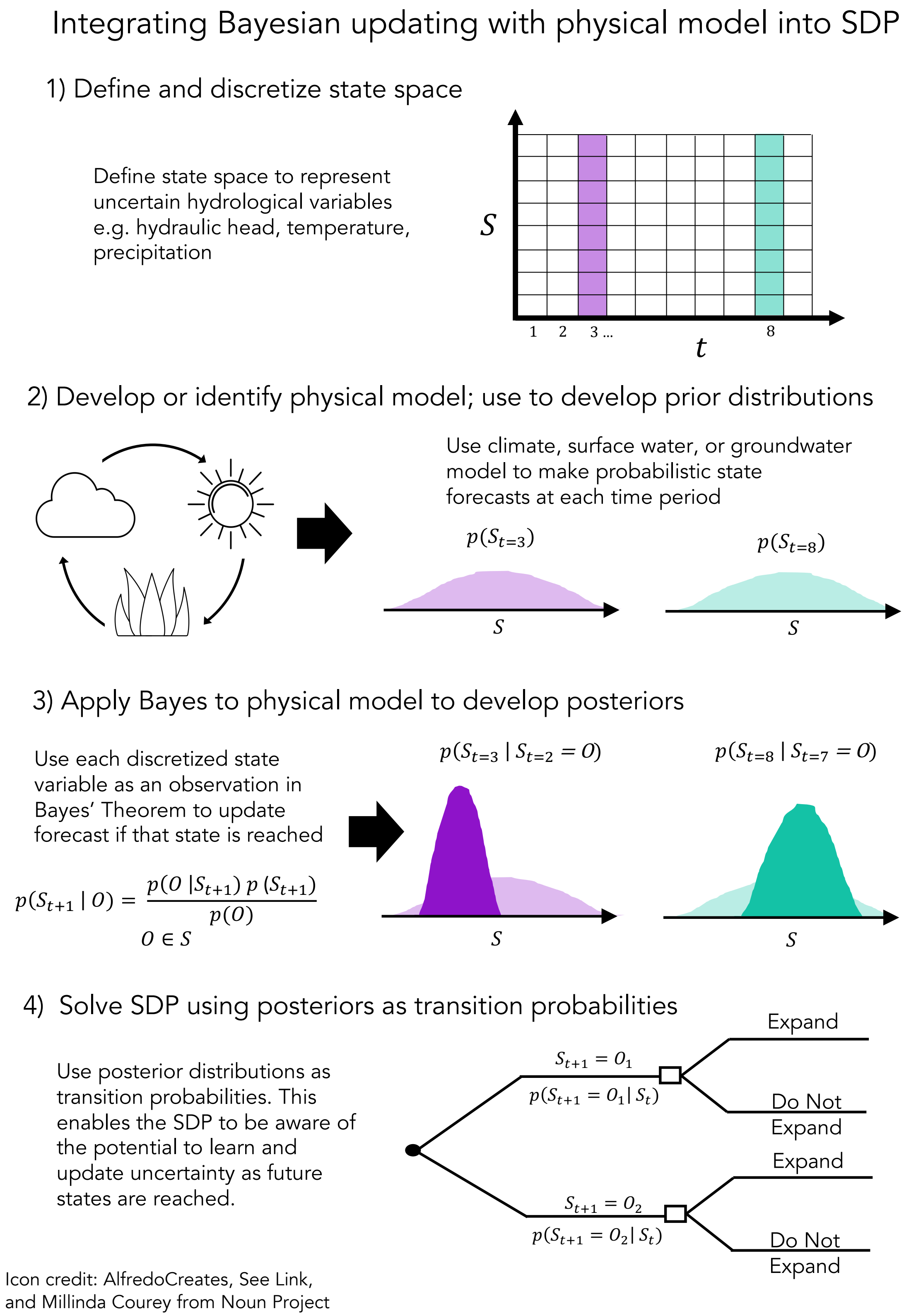

Figure 2-3: Schematic demonstrating the method for integrating probabilistic forecasts for uncertain hydrological variables into an SDP using Bayesian inference on a physical model

this is used in Chapter 5 to address model uncertainty, or disagreement across models with different structures, in climate change projections.

Third, Bayes' Theorem, shown in equation 2.2, is applied to update the prior distributions developed in step 2 with a new observation. The new observation corresponds to a specific state in the hydrological state space defined in step 1. The reasoning is if the system reaches a state s at time t, then s will be an observation about the system state that can be used to update future predictions. For example, say mean decadal temperature is 26°C at the beginning of the planning period with an expected value of 1.5 °C increase after 40 years. If after 40 years, 2.5 °C of warming are observed, this suggests a higher than expected rate of warming. Bayesian updating allows us to use this observation to update the original forecast to reflect faster warming. As with the prior, the specific implementation varies depending on whether parameter or model uncertainty is addressed; see details in Chapters 4 and 5 respectively. The updating is performed for each feasible state in each time period, with the state corresponding to a hypothetical, future observation.

$$p(S_{t+1}|O) = \frac{p(O|S_{t+1})p(S_{t+1})}{p(O)} \quad O \in S \tag{2.2}$$

Finally, the posteriors are embedded into the SDP as the transition probabilities, with each transition probability $p(S_{t+1}|S_t)$ equal to the corresponding posterior $p(S_{t+1}|O)$ where $O = S_t$. The Bellman equation is then solved using recursion. This process can be understood as a decision tree, as depicted in Figure 2-3. In each time period, a new observation is made, the transition probabilities updated to reflect an updated forecast, and then an action chosen for that time period. Although the transition probabilities reflect 1-step transitions from one time period to the next, the recursion enables optimal policies to be developed that take into account uncertainty over the entire planning horizon. Further, the use of the Bayesian updated posteriors as transition probabilities enables the optimal policies to account for the potential for learning as new observations are collected over time.

2.2 Integrated modeling and risk profiles

Once the uncertainties are classified and the corresponding analysis tool selected, they are incorporated into an integrated modeling approach depicted in Figure 2-4. This analysis is completed in four main steps. First, a hydrological or climate model is used to characterize

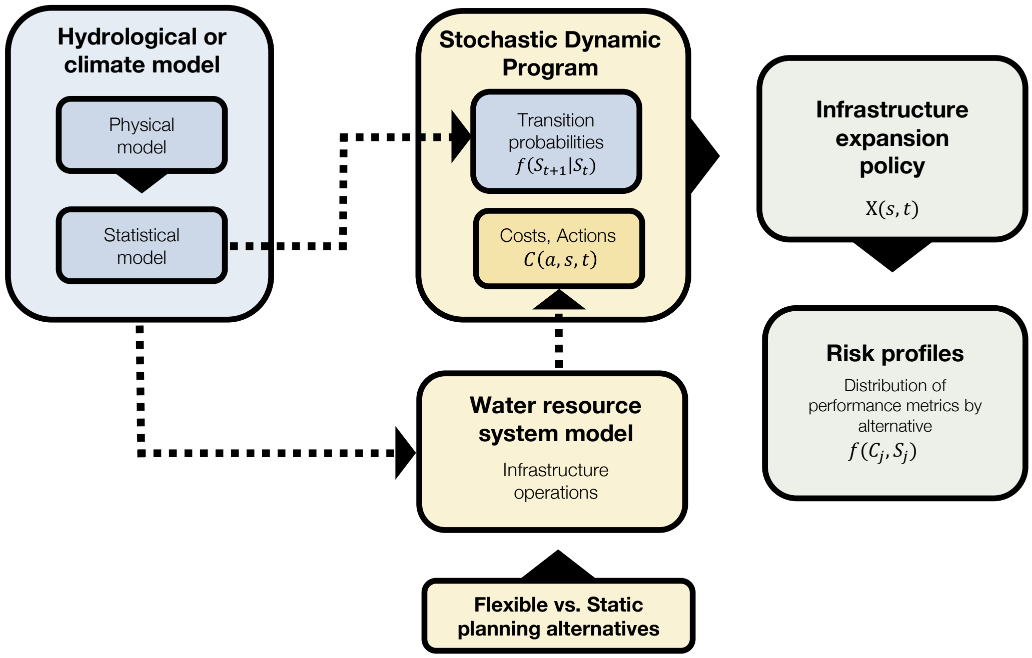

Figure 2-4: Schematic demonstrating the method for integrating probabilistic forecasts for uncertain hydrological variables into an SDP using Bayesian inference on a physical model.

non-stationary transition probabilities in an SDP; this step is described in detail in the previous section. Second, flexible infrastructure plans or designs are developed as alternatives to traditional static, robust approaches. Third, the impacts of different infrastructure alternatives on a water resource system are evaluated to characterize the SDP costs and actions. Finally, the optimal policies developed by the SDP are used to simulate and compare the performance of the different alternatives against key performance metrics. These steps are described below.

Flexible infrastructure alternatives

Flexible infrastructure plans or designs are developed as alternatives to traditional static plans; these are tailored to the planning problem at hand. Flexibility in infrastructure can take a variety of forms. Flexibility in planning can include flexibility in the timing, location, or type of infrastructure brought online. For example, a staged development approach in which capacity is added modularly in stages rather than all at once can trade off cost savings due to economies of scale in large infrastructure projects to prevent over building capacity. Flexibility can also be designed into physical infrastructure itself so that it can be more easily retrofitted in the future. For example, designing a dam that can be increased in height in the future enables flexibility in reservoir storage volume; this is assessed in Chapter 5. A RO desalination plant can be designed modularly so that extra RO modules can be added to increase capacity in the future; this is assessed in Chapter 3. In the applications in this dissertation, we consider flexibility in volume of capacity and in timing of capacity. In the surface water applications in Chapters 3 and 5, the planning question is focused on volume of capacity is needed in order to meet demand given uncertainty in supply; therefore, the designed flexibility is in the volume of capacity. In the groundwater application in Chapter 4, it is known that new capacity will be needed in the future and the question is when the investment will be needed in order to prevent reliability outages; in this case the flexibility is in the timing of capacity. For all of the applications, the flexible option to add additional infrastructure capacity is identified and designed up front. Then, the policy for if and when to exercise the option is determined by the SDP.

Water resource system model

In addition to the transition probabilities and state space definition, the SDP formulation requires definitions of the actions and costs. The actions can include both 1) which infrastructure alternative is chosen in the first time period and 2) at what point the flexible option is exercised if available. The SDP also requires estimates for the costs associated with a particular action in a certain state of the system. The costs can be broadly defined to include a variety of performance metrics of interest to the water planner. In the applications in this dissertation, we have included the capital and operating costs of the infrastructure itself, as well as damages incurred if water supply reliability targets are not met. Water shortages are estimated using a water resource system model, which combines hydrological models with infrastructure operation models. For example, in the climate change example in Mombasa in Chapter 5, a rainfall-runoff model is used to estimate monthly streamflow time series. Then, a dam operation model with operating rules for releasing flows depending on reservoir storage is used to assess whether supply meets demand in each time period and if not, what volume of shortages are incurred. We do not attempt to optimize the operating rules. This analysis is repeated for each possible climate state. The shortage volumes are multiplied by a shortage penalty value, estimated using economic models of the damages caused to society by water shortages. These costs are summarized in equation 2.3

$$C(s, a, t) = Capex(a) + Opex(a, s) + D * U(a, s, t) \tag{2.3}$$

where C is the single-period cost, s is the state of the system including the uncertain hydrological state variables as well as available and planned infrastructure capacity, a is the action which includes building or expanding infrastructure capacity, t is the time period, $Capex$ is the capital costs associated with infrastructure action a, $Opex$ is the operating costs associated with existing and new infrastructure, D is the water shortage penalty representing economic damages for water shortages, and U is unmet demand as a function of the hydrological state and existing and new infrastructure as measured by the water resource system model.

Forward simulation and risk profiles

Finally, after solving the SDP to develop the optimal polices for exercising the flexible infrastructure alternatives, we assess their performance. Monte Carlo simulation is applied to 1) the transition probabilities in the SDP to create time series for the uncertain hydrological state variable(s) and 2) any statistical, low-learning potential uncertainties. The optimal policy is then applied to determine if and when the flexible expansion option is exercised in each simulated time series. The costs and water shortages of the expansion are estimated using the water resource system model. This generates distributions of cost and shortages for each infrastructure alternative that are used to assess the strengths, weaknesses, and trade-offs of different infrastructure planning approaches. For deep uncertainties that rely on scenarios, the simulation analysis is repeated to assess how the performance distributions change under different scenarios. Developing distributions for performance rather than a single estimate enables us to assess upside and downside risk, regret, and other decision criteria. These measures are used to assess the value of flexibility, enabling planners to decide if upfront investments in flexible are worth the cost.

Chapter 3

Desalination planning under multiple, diverse uncertainties during Melbourne's Millenium Drought

This chapter has been adapted from a previously published paper: Sarah M. Fletcher, Marco Miotti, Jaichander Swaminathan, Magdalena M. Klemun, Kenneth Strzepek, and Afreen Siddiqi. "Water Supply Infrastructure Planning: Decision-Making Framework to Classify Multiple Uncertainties and Evaluate Flexible Design." Journal of Water Resources Planning and Management 143 (10), 2017.

Abstract: Urban planners face challenges in water infrastructure development decisions due to short-term variation in water availability and demand; long-term uncertainty in climate and population growth; and differing perspectives on the value of water. We classify these multiple uncertainties and develop a decision framework that combines simulation for probabilistic uncertainty, scenario analysis for deep uncertainty, and multistage decision analysis for uncertainties reduced over time with additional information. We apply this framework to a case from Melbourne, Australia where a drought from 1997 to 2009 prompted investment in a $5 billion desalination plant completed in 2012 after the drought ended. Our results show opportunities for significant reduction in capital investment using flexible design. Building no infrastructure is best in most simulations. However, in 10% of simulations building no infrastructure leads to regret of greater than $10 billion compared

to a small, flexible desalination plant. Scenario analysis for deep uncertainties underlines the significant impact of assumptions about the future and also on value judgments about the cost of water scarcity in evaluating infrastructure performance.

3.1 Introduction

Urban water planners face the decision of how much water infrastructure to build in order to reliably meet demand for high-quality water while minimizing cost to meet budget constraints. The challenge of balancing the tradeoff between shortage risk, cost, and environmental protection is compounded by several critical uncertainties. Urbanization is driving population growth in many cities at rapid but uncertain rates; natural variation in annual runoff is high and expected to increase due to climate change in many regions [78]; energy price volatility and variable maintenance requirements drive cost risk for desalination and other energy-intense infrastructure options. Additionally, numerous water supply systems in many industrialized countries are reaching the end of their planned lifetimes, prompting further need for infrastructure investment.

Most urban water supply infrastructure (such as distribution pipelines, treatment plants, and reservoirs) in Australia, the US, and other industrialized countries was built between the 1930s and 1980s, before sophisticated risk and decision analysis methods had been developed for practical use [149, 49, 52]. Traditionally, planners developed a long-term demand forecast and long-term supply forecast, and added a safety factor to account for uncertainty [149]. This approach can lead to overdesign when demand ends up being lower than forecasted. If demand exceeds the forecast, society can face economic impacts due to unserved demand, environmental degradation, and expensive measures for building additional infrastructure in short time frames.

Since the 1980s, reliability, or outage frequency, has been emphasized as a risk-based metric for assessing water supply system performance [67]. More recently, researchers and planners have developed strategies to improve resilience and robustness under uncertainty. Early work focused on the use of adaptive management to operate water supply systems more flexibly to ensure resilience under extreme operating conditions [115, 47]. Adaptive management requires planners to change from a predict-then-act approach to a learn-then-adjust approach [121]. A related strategy is flexible infrastructure design, which allows planners to respond to future uncertainties. The use of engineering options, in which infrastructure is designed so that it can be modified or expanded in the future depending on how supply and demand evolve, provides flexibility that can reduce reliability and cost tradeoffs in water supply systems [168, 33]. The application of an EOA, including staged deployment, has been demonstrated in several recent studies on design of water distribution systems [101], urban water systems [37, 53, 162], water treatment investments [178], and dam investments [80]. Engineering options can be compared and evaluated using multi-objective decision analysis to incorporate multiple planning goals and evaluate flexible design options as uncertainties unfold over multiple planning stages [33].

Recent methods have also been developed for new infrastructure planning that is robust to "deep uncertainties" such as climate change. The likelihoods of deep uncertainties cannot be accurately quantified using historical data, rendering probability-based risk assessment challenging or inappropriate [60, 108]. The goal is to generate and evaluate planning strategies that are robust to a range of future outcomes. For example, RDM uses Latin hypercube sampling to generate many possible futures scenarios across multiple uncertainties, assumes equal likelihood of each scenario, and selects strategies that meet threshold performance criteria across a large percentage of scenarios [93, 92]. Info-Gap theory, in contrast, develops increasingly large multi-dimensional uncertainty sets and identifies the solutions that meet threshold performance criteria for each uncertainty set [14]. Decision scaling links decision analysis with bottom-up climate vulnerability analysis, identifying climate-driven action thresholds without relying on general circulation models to generate climate scenarios [19]. Such approaches have been widely applied to problems in water resources planning in various countries [122, 39, 87, 110]. Climate change and other deep uncertainties should be integrated into a water resources modeling framework that accounts for the full range of uncertainty planners face [135].

While scenario analysis has been demonstrated to be a powerful planning tool for urban water managers facing deep uncertainties and varying stakeholder concerns [94], this does not preclude the use of probabilistic approaches for different, more easily modeled uncertainties. Population growth, which is more easily modeled statistically, is expected to have a larger impact on water resource systems to mid-century than climate change [164, 144, 142, 48]. The stationary statistical variation in rainfall, which can be modeled stochastically, often drives uncertainty in the short- to medium-term more than climate change [95, 42].

In this paper, we build on traditional decision analysis and deep uncertainty methods for water supply planning by developing a framework to classify and model multiple uncertainties of different natures. It enables water supply planners to quantify statistical uncertainties that can be appropriately quantified and to assess the impacts of different, deep uncertainties on a risk profile using scenario analysis. It also identifies which uncertainties enable learning over time and incorporates them into a multistage decision analysis model. This model enables the evaluation of real options such as staged deployment where planners learn as uncertainties unfold and utilize flexible options if and when they are needed.

We apply the method to a case of urban water supply planning in Melbourne, Australia. The Millennium Drought in Southeast Australia from 1997 to 2009 motivated our work. Melbourne's water supply system comprises a network of 10 storage reservoirs with a total of 1,812 million cubic meters (MCM) of storage. Net average annual inflows (evaporation and losses subtracted) were 571 MCM between 1926 and 2014 and demand was 401 MCM in 2014/2015 [104]. This results in a storage-to-annual-runoff ratio of 3.2, which indicates a highly managed system. Catchment-level stream flow management plans require minimum environmental flows to be met [104]; environmental flows ranged from 100 to 410 MCM between 1995 and 2011 [97]. Minimal groundwater is used [97]. A single bulk wholesaler, Melbourne Water, is responsible for harvesting, storage, and treatment.

After more than a decade of below average rainfall, reservoir storage for the city reached a record low of 25.6% of capacity in 2009 [97]. This led to a range of demand management efforts including efficient appliance installations, reduced environmental flows, water restrictions for outdoor uses, a domestic rainwater tank installation program, and treated wastewater recycling. There were also two large infrastructure investments: the 150 MCM per year Wonthaggi RO desalination plant and the 100 MCM/year maximum capacity Sugarloaf pipeline at capital costs of $5 billion and $550 million, respectively, able to provide up to about 40% of the city's demand [58]. However, the drought ended before the desalination plant was completed, leaving the plant unused for years. Several studies discuss the political pressure on Melbourne Water and the Victorian government, a detailed timeline of actions taken, and the institutional decision-making process in responding to the drought [49, 58, 126, 97]. Melbourne's reservoir system and Wonthaggi plant are illustrated in Figure 3-1.

This work addresses the question: given similarly uncertain and dire situations like those

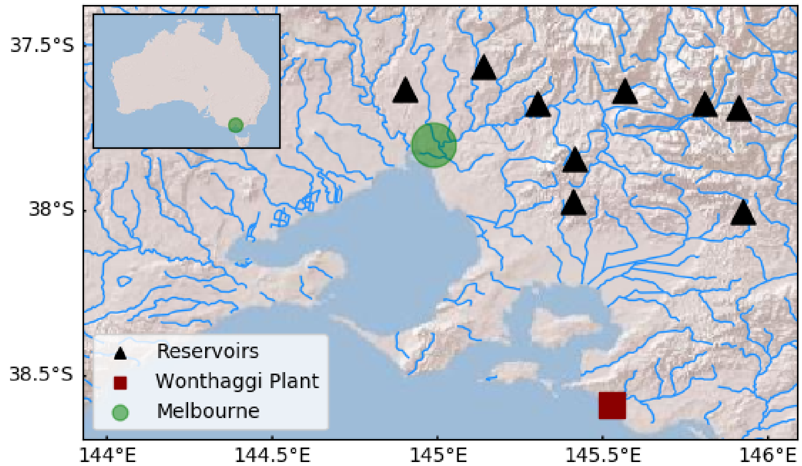

Figure 3-1: Melbourne study area map showing locations of reservoirs, streams, Wonthaggi plant, and city center.

Melbourne faced in 2007 and the inherent tradeoff between cost, supply risk, and environmental protection, what approach can water planners use in evaluating infrastructure investments when facing multiple uncertainties of different natures? A decision framework using classification and incorporation of multiple uncertainties is applied in order to 1) evaluate and communicate the cost and water supply risk of proposed infrastructure alternatives, and 2) identify the best infrastructure alternative based on a planner's risk preferences across simulated water supply futures. We do not present a single best solution, as that would require value judgments and preferences from stakeholders and planners. Rather, we present results for a range of sample preferences to demonstrate the usefulness of the framework. The remainder of the paper is organized as follows. Section 3.2 describes the methods used: the uncertainty framework is presented first, followed by a description of its application to Melbourne. Key results and conclusions are presented in Section 3.3 and Section 3.4, respectively. More detailed descriptions of the methods and additional results are shown in Appendix A.

3.2 Modeling approach

Decision Framework for Multiple Uncertainties

Many uncertainties simultaneously impact water supply infrastructure planning including annual reservoir inflows, population growth, energy prices, the cost of water supply shortages, and climate change. We develop a framework for decision making under multiple uncertainties, illustrated in Figure 2-1 in Chapter 2.

The first step in the framework is to classify uncertainties along two dimensions: whether they are deep or statistical, and whether there is high or low potential for learning over time. Deep uncertainties are those for which the likelihood of the outcomes cannot be determined; they are modeled using scenarios analysis in order to avoid estimating likelihood. In this context, scenario analysis refers to varying the value of uncertain parameters in order to understand the impact of their uncertainty on the results. Note that while scenarios are not explicitly probabilistic, the choice of values does assign some implicit probability to those outcomes; this is important to recognize in all deep uncertainty methods. Statistical uncertainties are those that can be estimated using data-driven probability distributions. Statistical uncertainties are modeled using Monte Carlo simulation in order to obtain the most precise risk profile. The high vs. low learning potential indicates whether, as the uncertainty is realized over time, additional observations meaningfully update the planner's expectations of the future. Based on updated expectations, planners decide to exercise or ignore flexible options. These uncertainties are therefore incorporated directly into a multistage decision analysis model [33], in which flexible options are optimally exercised or ignored. This allows the full value of flexible options to be modeled. Uncertainties that do not yield meaningful updates on expected payoffs as observations are made over time can be analyzed more efficiently by varying the inputs across model runs.

This uncertainty classification addresses the level of uncertainty [166] and the potential for learning over time. Note that the level dimension can also incorporate ambiguity, or uncertainties that arise through differences in stakeholder perspectives [20, 90], such as value judgments about the cost of water shortages. Uncertainties arising from ambiguity are similar to deep uncertainties in that they are not appropriate for probabilistic analysis, so scenario analysis is used instead. Different objective functions can be used to represent different preferences or risk profiles. For instance, a risk-averse planner may prefer to invest in water supply infrastructure that often sits idle as an insurance policy against drought that minimizes shortage risk. While there is a large literature on eliciting and incorporating stakeholder values into decision analysis [137, 59, 63], such analysis is not included in this paper. Rather, a sample objective function and a few scenarios comparing alternative objective weights are used to demonstrate the method. Additionally, other dimensions of uncertainty, such as the location of uncertainty within a decision-making process, structural uncertainty, and observational uncertainty, are not addressed here.

In the second step, a model of the water system is combined with the decision model to evaluate and compare infrastructure alternatives. These infrastructure alternatives can be generated through a screening model or planner input. The water system model is simulated to generate the distribution of cost and water supply risk for each infrastructure alternative over all statistical uncertainties. Statistical uncertainties with high learning potential are incorporated into the decision analysis model explicitly so that flexible options can be exercised in response to new information. The decision model ranks the infrastructure alternatives according to an objective function for each simulation run, resulting in a distribution of "best" infrastructure alternatives across simulated variables. Scenario analysis is then used to repeat the simulation process for different sets of input variables representing deep uncertainties to assess the impact of scenarios on the risk profile.

3.3 Application to urban water supply planning in Melbourne, Australia

This analysis framework is applied to an illustrative example from Melbourne, Australia, where planners in 2007 decide what, if any, additional supply investments should be made over a 30-year planning period (the approximate lifetime of an RO plant). Key uncertainties are identified and classified. Infrastructure alternatives are chosen based on those considered by Melbourne's water planners in 2007, with additional flexible alternatives designed for comparison. A model of Melbourne's water system is developed using a simple hydrological model and demand forecasts. A decision analysis model is then used to evaluate the infrastructure alternatives, including some with flexible expansion options, based on an objective function that considers lifetime costs and water shortages.

Table 3.1: Methods used for key uncertainties in analysis based on uncertainty classification framework

Uncertainty	**Classification**	**Justification**
Short-term variability in streamflow	Statistical; low learning potential	Well-characterized by historical data; stationarity assumption appropriate over short time scales
Population growth rate	Statistical; high learning potential	Well-characterized by existing demographic forecasts; early changes in growth rate highly predictive of future growth
Electricity price	Deep uncertainty	Influenced by deeply uncertain factors such as national and international policy and markets.
Water shortage penalty value	Deep uncertainty	This is an ambiguity, or uncertainty arising from differences in stakeholder perspective
Demand per capita	Deep uncertainty	Influenced by deeply uncertain factors such as policy, citizen behavior, and technology adoption

Uncertainty classification

Five uncertainties, listed in Table 3.1, are included in this analysis. They were chosen because of their high degree of uncertainty and potential for impact on Melbourne's planning decisions; however, they are not comprehensive. Certain uncertainties were excluded, such as the potential for desalination technology costs to decline over time, because initial analysis of historical data suggested they were unlikely to impact planning decisions on a 30-year timeline. Other uncertainties, such as climate change, future agricultural production, policy changes, structural and observation uncertainty, could be included in future work. The included uncertainties are classified as indicated in Table 3.1 with brief justifications. Decisions to classify uncertainties using the framework developed in Chapter 2 ultimately rely on analyst judgment but are informed by analyses of available historical data and forecasts. We base the analysis on historical inflow data [104], historical and forecasted population growth [10], and historical and forecasted electricity price [2]. Further details are available in Appendix A.

Table 3.2: Definitions for the six infrastructure alternatives evaluated and compared in the decision-modeling framework. S3 and S5 were developed to compare a staged deployment approach to the full, upfront deployment approach used in S4 and S6.

Infrastructure Alternatives	Capital Expenditure (M$)	Capacity (MCM/year)
S1: No Build	0	0
S2: Pipeline and irrigation upgrade	1,002	Variable: Max 100
S3: Small RO plant with expansion option	2,045 [+1,095]	Firm: 75 [+ 75]
S4: Large RO plant	2,900	Firm: 150
S5: Small RO plant with expansion option; Pipeline and irrigation upgrade	3047 [+1,095]	Firm: 75 [+ 75] Variable: Max 80
S6: Large RO plant; Pipeline and irrigation upgrade	3902	Firm: 150 Variable: Max 80

Infrastructure alternatives

We design and evaluate six infrastructure alternatives comprised of combinations of three projects: a 150 MCM/year RO plant based on the Wonthaggi plant, a 100 MCM/year capacity pipeline and accompanying irrigation system upgrade based on the Sugarloaf pipeline and accompanying upgrades, and a 75 MCM/year RO plant designed with a flexible option to expand to 150 MCM/year if desired. The smaller (75 MCM/year) desalination plant was not considered by Melbourne Water in 2007; it was included here as an alternative to assess the value of staged deployment. The flexible design requires the plant site to be sized to fit twice as many membrane modules as needed before the expansion, incurring additional capital costs upfront in exchange for the option to expand cheaply and quickly later. The no-build alternative (S1 in Table 3.2) is included as a baseline option where no new infrastructure is developed.

The desalination plants incur both high capital costs and high operating costs. The operating costs are high due to the energy intensity of seawater desalination and membrane replacement requirements. In addition to substantially lower capital costs, the pipeline and irrigation upgrade also incurs much lower operating costs; pumping is the largest component. The desalination plants, however, provide firm capacity; they can reliably provide the maximum design capacity during a dry year. The pipeline system is market-based: farmers whose irrigation systems have been upgraded to be more efficient sell excess water to the utility at their discretion. Farmers are less likely to provide water during dry years, so it is unlikely that the full 100 MCM/year is available each year. This dynamic is approximated by assuming a correlation between inflows to Melbourne's reservoir system and water available from the pipeline, with 80 MCM available during average wet years and no water available during dry years. Cost estimates (capital expenditures, fixed operating costs, and variable operating costs) are developed for each infrastructure alternative using cost data from the Sugarloaf pipeline project, cost information on the Wonthaggi plant, cost data from comparable RO plants, and input from desalination experts. Details are available in section B of the Supporting Information.

Water System Model

A water system model is developed using a water balance approach to model reservoir storage and water supplied to end users from both the existing reservoir system and new supply infrastructure. This model estimates the annual cost and water shortages (i.e. unserved demand) over a 30-year period starting in 2007 for each infrastructure alternative. Monte Carlo simulation is used to develop distributions for these estimates based on uncertainty in inflows and population growth.

The main components of the water balance are: net reservoir inflows (inflows minus evaporation), demand from end users, water imported from new infrastructure, and environmental outflows. To model future inflows, 100,000 synthetic annual 30-year inflows are generated using anauto-regressive moving average (ARMA) time-series model fit to historical inflow data dating back to 1926. This approach captures the year-to-year autocorrelation observed in runoff. It assumes inflows to be a stationary stochastic process over the 30-year planning period. Scenario analysis is used to vary the mean and variance of this process based on estimates of climate change impacts on runoff in Australia [150]. This is a simple approach; climate change is not a focus of this paper. Future work evaluating longer planning periods could use more sophisticated statistical approaches such as downscaling from general circulation models. Annual water demand is modeled as the product of population and demand per capita. Population projections from the Australian Bureau of Statistics for the city of Melbourne are used, ranging from 50,000 to 150,000 people per year [10]. The base case demand per capita of 100 kiloliters (kL)/person/year is based on historical demand data and is varied using scenario analysis to assess the impact of demand reduction measures; future work could assess and compare demand-side alternatives directly. Water is imported from any new infrastructure capacity if reservoir storage levels go below one of two thresholds. Pipeline water is imported below an intervention threshold of 980 MCM and desalination water is imported below an emergency threshold of 580 MCM, the maximum allowable drawdown. These thresholds are set by Melbourne Water [106] and used in other studies of Melbourne's water system [161]. In this paper, water shortage is defined as water demand that cannot be met without reducing demand or withdrawing below the emergency threshold. The water system model aggregates the individual reservoirs and uses an annual time step. This approach is appropriate to demonstrate the new method developed in this paper and given the capacity-expansion focus of the decision model [11] and the high intra annual storage in the system. More details on the water system model, including the assumed operational rules, are available in Appendix A.

Decision Analysis Model

The decision model uses the estimates for cost and water shortages from the water system model to evaluate the six infrastructure alternatives (Table 3.2) over a 30-year planning period. For each synthetic 30-year inflow series, the model ranks the six infrastructure alternatives using multi-stage decision analysis, which is frequently used to evaluate real options [33]. The model can be understood as a decision tree, in which the population growth rate has a probability of going up or down in each 10-year planning stage. In the two infrastructure alternatives with flexible desalination design, S3 and S5 (Table 3.2), the planner can react to change in population growth by deciding to exercise the real option of expanding a small desalination plant. The model chooses the infrastructure alternative and desalination plant expansion timing, where applicable, that minimizes the following objective function:

$$E[TotalCost_i] = ENPV[Cost_i + Penalty * WaterShortage_i] \tag{3.1}$$

where E denotes expected value; i is the choice of infrastructure alternative and expansion strategy; $Cost$ is the total of capital costs and operational expenditures incurred from the infrastructure alternative over the planning period; $WaterShortage$ is the total volume of water shortages from years where water demand without conservation or environmental flow reductions exceeds available water supply, also interpreted as water supply vulnerability [67]; $ENPV$ is expected net present value; and $Penalty$ is a cost incurred by the decision-maker for each MCM of water shortage during the year of the shortage. A monetary penalty for shortages does not exist in reality in Melbourne or most municipal water utilities. Instead, the cost of water shortages is borne by society as economic damages. The penalty value can therefore be interpreted as the planner's degree of risk aversion to water supply vulnerability. A base case value of million US dollars (M$) 25 /MCM is chosen to be about 50 times higher than the bulk usage price of desalinated water ($ 0.55 /m3) in Melbourne [106] and consistent with previous work [79, 133]. Using scenario analysis, different penalty values up to M$ 250 /MCM are evaluated, consistent with prices in other previous work [96]. $ENPV$ is calculated using a discount rate of 7%, which is in the middle of the range typically used by government agencies to evaluate projects [66]. Note that this representative objective function is intended to demonstrate the method and does not reflect real stakeholder preferences. Use of this method in future planning could incorporate stakeholder input on the value of the penalty through a collaborative stakeholder engagement process.

Finally, after the decision model ranks the infrastructure alternatives based on the expected value of total cost, Monte Carlo simulation is used to randomly choose a single population growth path for each model run. This allows us to see, across many synthetic inflow and population growth time series, how the infrastructure alternative chosen based on expected value performs against simulated actual conditions. For example, the decision model might choose to build no additional infrastructure because the expected shortages are low; however, there is a small probability that high population growth could lead the actual shortages to be high. Using this approach, results that show the performance of each infrastructure alternative across many realizations of the simulated uncertain variables, reservoir inflows and population growth, are presented. Further details on the decision analysis model are available in section C of the Supporting Information.

3.4 Results

First we present results showing the impact of the statistical uncertainties, reservoir inflows and population growth. This includes results from the water system model showing the cost and water shortage risk of each infrastructure option (Figures 3-2 and 3-4) as well as results of the decision model (Figure 3-3). These results are shown as distributions, since Monte Carlo simulation is used for statistical uncertainties. Then, results showing the impact of deep uncertainties using scenario analysis are presented. Figure 3-5 shows how the distribution-based results obtained from addressing the statistical uncertainties are shifted when scenario-based deep uncertainties are also addressed.

Statistical uncertainties

Figure 3-2 summarizes the model results for cumulative water shortages and infrastructure cost for each of the infrastructure alternatives across 100,000 water supply simulations using bagplots [141]. The bagplot is an analog to the boxplot for bivariate data [141]. For each infrastructure alternative except no-build, the center point marked with an asterisk is the Tukey median [45]; the inner, dark-colored shape is the "bag" which contains 50% of the data, similar to the inner section of a boxplot; and the outer, light-colored shape is the convex hull that encompasses the rest of the data excluding outliers. These plots show the distribution of cost and water supply risk faced as a result of the statistical uncertainties addressed, reservoir inflows and population growth. The no-build alternative costs nothing but incurs the greatest shortage risk, with the median total shortage spanning the 30-year period at 260 MCM. Cumulative shortages greater than 2,000 MCM (over the 30-year period) occur in 20% of simulation runs. The pipeline alternative (S2) consistently imposes a cost of close to $1 billion, and decreases the shortage risk. The four infrastructure alternatives that include a desalination plant all increase the average cost and cost variability while decreasing the shortage risk further. Interestingly, the median water shortage for all four alternatives with desalination is 0, with 90th percentile shortages all on the order of 1,000 MCM over the 30-year analysis period. Within these four, the alternatives that have more built infrastructure capacity see modest reductions in water shortage risk for more significant cost increases. Most notably, the alternative of the small plant with expansion option (S3) has a very similar water shortage risk profile to the large plant (S4), as shown by the width of the inner bag, with median cost about $1 billion lower, again demonstrating the value of staged deployment under uncertain demand. The same relationship is true of the infrastructure alternatives with desalination and pipeline. This value is also demonstrated by the variation in utilization of the expansion option: the option is exercised in about

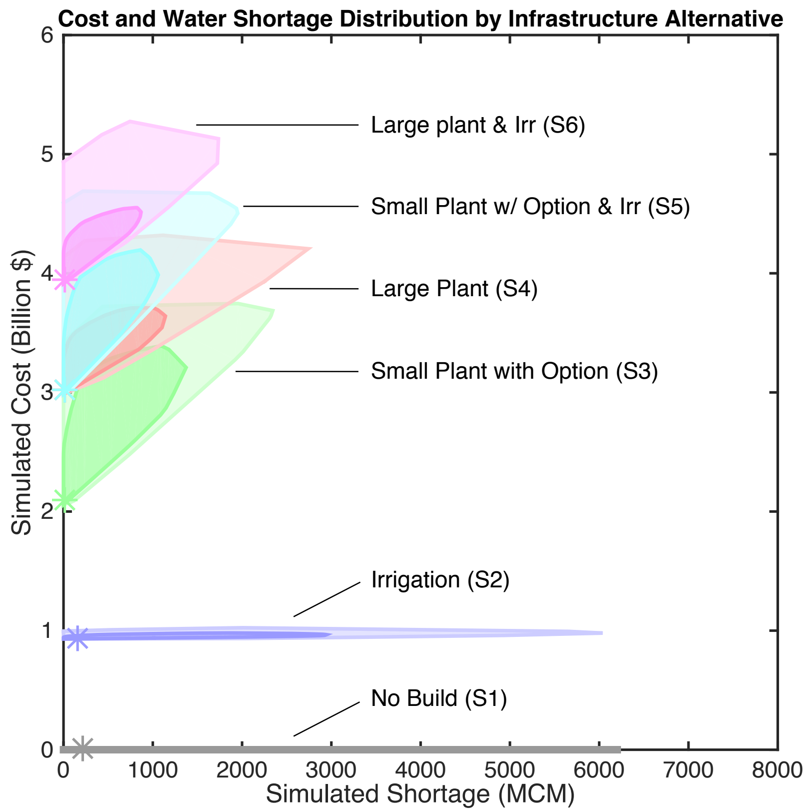

Figure 3-2: 'Bagplots' visualize the distribution of infrastructure cost and total water shortage across a random sample of 1,000 total water supply simulations for each infrastructure alternative. Because the no-build alternative always incurs zero cost and is therefore univariate, the plot shows the median shortage and a line that spans the range of shortage between the 0th and 99th percentiles, which is analogous to the convex hull in the bagplots. Building desalination capacity increases cost while mitigating risk of high magnitude shortages. Flexible design can mitigate shortage risk at lower cost.

45% of simulations in the small plant without pipeline alternative (S3) and about 40% of simulations in the small plant with pipeline alternative (S5).

Across all of the infrastructure alternatives, more than 80% of the years simulated incurred no water shortage at all. Large annual water shortages of >100 MCM were more common than smaller shortages. These large annual shortages are concentrated in the second half of the 30-year period, as the population growth leads to higher demand in later years. This has important implications for the capacity factor of the built infrastructure as well as timing the decision to build new infrastructure. The median number of years that the built infrastructure is used is between 4 years and 6 years across all the infrastructure alternatives. This means that any infrastructure that is built is likely to be used for 20% or less of its lifetime. This is because the total water shortage incurred over the 30-year planning period is typically concentrated in a small number of years that incurred extreme lows in runoff coupled with high demand.

The decision model evaluates the six infrastructure alternatives based on the overall cost, which includes both infrastructure cost and penalties for water shortages over a 30-year period. In addition to choosing a best alternative based on expected values, it also calculates the simulated payoff for each alternative in each model run, and ranks the alternatives according to this simulated payoff. A simple way to communicate and compare the infrastructure alternatives is to compare the rankings, shown in Figure 3-3 for 100,000 simulations of the base case. The no-build alternative (S1) is the best performing infrastructure alternative in more than 50% of cases; however, it is the worst performing alternative in more than 30% of cases. This underlines the risk of planning based on a single forecast. At the other extreme, the large plant plus pipeline alternative (S6) performs the worst in more than 60% of cases and rarely performs within the top half of rankings. Notably, an interesting result is the flexible small desalination plant (S3): despite performing the best in only about 20% of simulations, this alternative performs in the top half of rankings in nearly 90% of simulations and never ends up as worst or second to last. This demonstrates the ability of paying a small premium for flexibility to mitigate downside risk significantly.

The total cost including shortage penalties incurred by each infrastructure alternative across the 100,000 inflow simulations were also analyzed and shown in Figure 3-4. The no-build alternative is the lowest cost in 50% of runs, with more than 40% of runs incurring zero total cost, indicating no water shortages over 30 years. However, the downside risk is significant; in 1% of runs the total cost of the no-build alternative is over $10 billion greater than the cheapest alternative. Interestingly, the pipeline alternative (S2) performs similarly to the no-build alternative, with about $1 billion higher cost in the low-cost half of simulations and lower cost in the high-cost half of simulations. This is due to the impact of the market-based system for water sales through the pipeline, demonstrating the limits of water markets to provide firm capacity when there is high correlation between drought in the two interconnected regions. The four alternatives that include desalination have high capital costs, but in more than 30% of simulations they incur cheaper overall costs than the no-build or pipeline alternatives. The small plant (S3) provides a mid-range capital cost

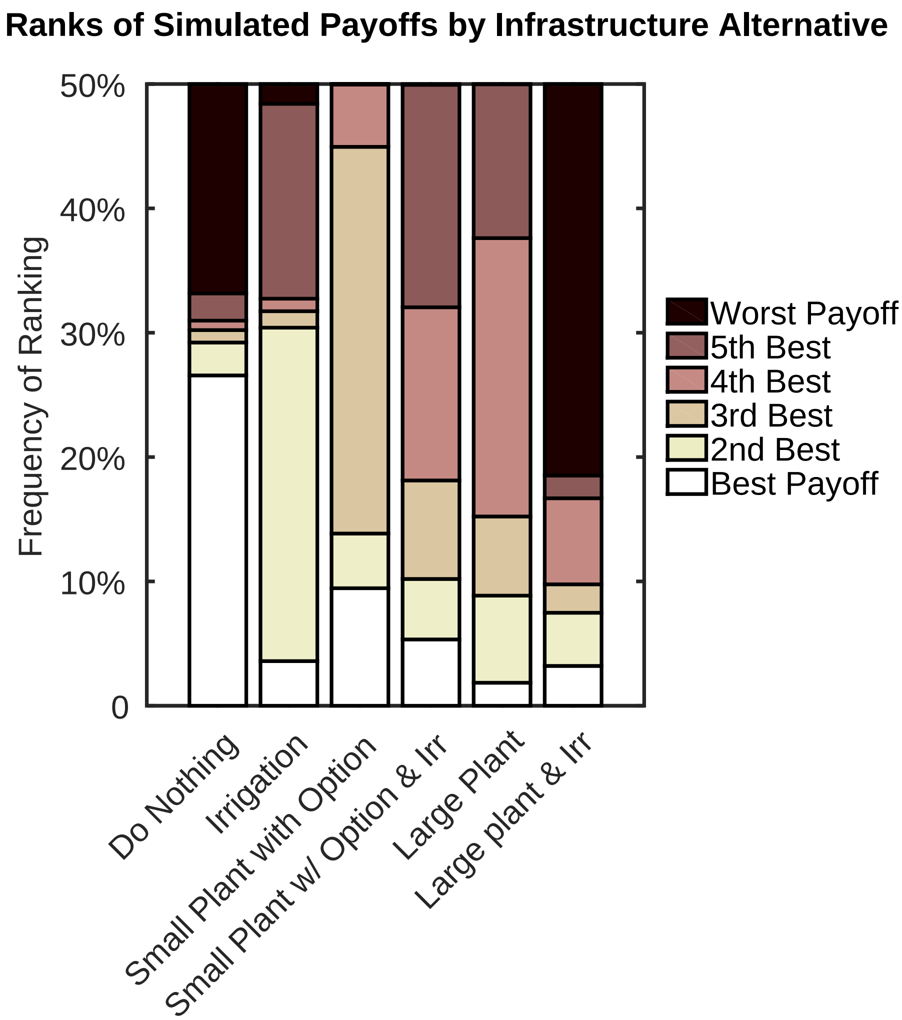

Figure 3-3: For each of 100,000 simulations, the simulated total payoff for each of the six infrastructure alternatives is calculated and used to rank the alternatives from best to worst. Doing nothing is best in more than half the simulations but also worst in more than 30% of simulations.

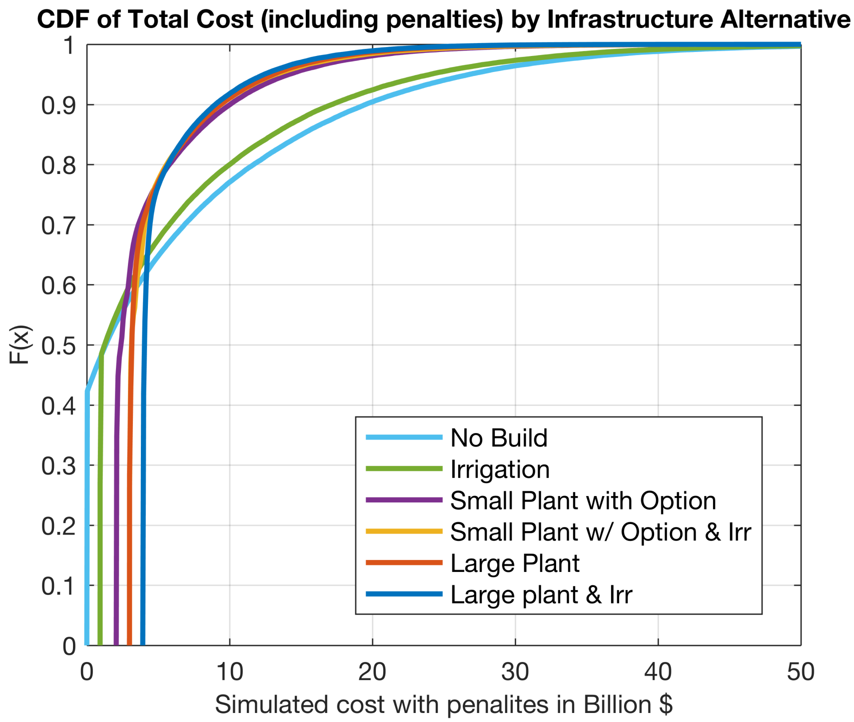

Figure 3-4: Cumulative density function (CDF) of the total cost including water shortage penalties by infrastructure alternative. In the median case, the no-build and irrigation alternatives perform best. However, they pose significant downside risk, with total costs about $10 billion higher at the 90th percentile. The small plant with option has the lowest cost of the alternatives with desalination in the lower cost half of runs and has a similar downside risk.

alternative that significantly mitigates downside risk through the use of a flexible option.

Deep uncertainties

So far, results have incorporated uncertainties arising from inflow variability and population growth, the two statistical uncertainties addressed. Now, scenario analysis is used to show the impacts of the deep uncertainties addressed: demand per capita, the shortage penalty value, and electricity price growth (see Table 3.1. Each bar in Figure 3-5 shows the frequency that the decision model selected each infrastructure alternative as the best across a set of 100,000 simulations. In the base case, indicated using an asterisk, the model chooses both the no-build alternative and the small plant (S3) about 40% of the time each. The results are highly sensitive to the penalty factor, shown in Figure 3-5 (a). The no-build alternative performs best in more than 95% of simulations when the penalty is reduced to M$ 5/MCM. Likewise, increasing the penalty makes alternatives with greater capacity more favorable.

Increasing the penalty to M\$ 50/MCM makes the no-build alternative best in about 25% of simulations down from 40% and the small plant with option plus pipeline best in 20% of simulations up from about 5%. Increasing the penalty by a full order of magnitude to M\$ 250/ MCM, consistent with the values in [96], increases the magnitude of this shift. The no-build alternative is chosen as best in less than 5% of simulations and the small plant with option plus pipeline (S5) is chosen in about 60%. It is interesting that the small plant with option plus pipeline dominates the distribution of best options over the large plant (S4). Both alternatives have 150 MCM of capacity without the expansion in (S5); however, half that capacity in S5 is variable rather than firm. This suggests that the value of flexibility from the expansion option outweighs the variability in some of the capacity in S5.

The model results are also highly sensitive to the demand per capita, shown in Figure 3-5 (b). Lowering the demand to 80 kL per capita per year substantially reduces the need for additional infrastructure, with the no-build alternative performing best in more than 95% of simulations. The high sensitivity to demand per capita suggests that demand-side conservation measures may be able to significantly reduce the need for supply infrastructure investments, especially if demand reductions are firmly available during dry years. This demonstrates the profound potential of demand management, and points to the need for more rigorous analysis of infrastructure expansion decisions in conjunction with demand management options. Results are relatively insensitive to the electricity price growth rate, shown in Figure 3-5 (c).

3.5 Discussion

The primary contribution of this paper is the development of a method that can be used to inform decision-makers making water supply infrastructure plans under multiple uncertainties. We develop a classification framework for uncertainties that enables the use of probability-based risk quantification and information gathering where appropriate, while leaving deep uncertainties to be addressed using scenario analysis. This approach allows us to evaluate and compare infrastructure alternatives, including those with flexible design, as well as demand-reduction strategies in a way that takes into account the diverse and multifaceted uncertainties water planners face. The use of simple yet information-dense visualizations of risk profiles can provide decision-support for policy makers.

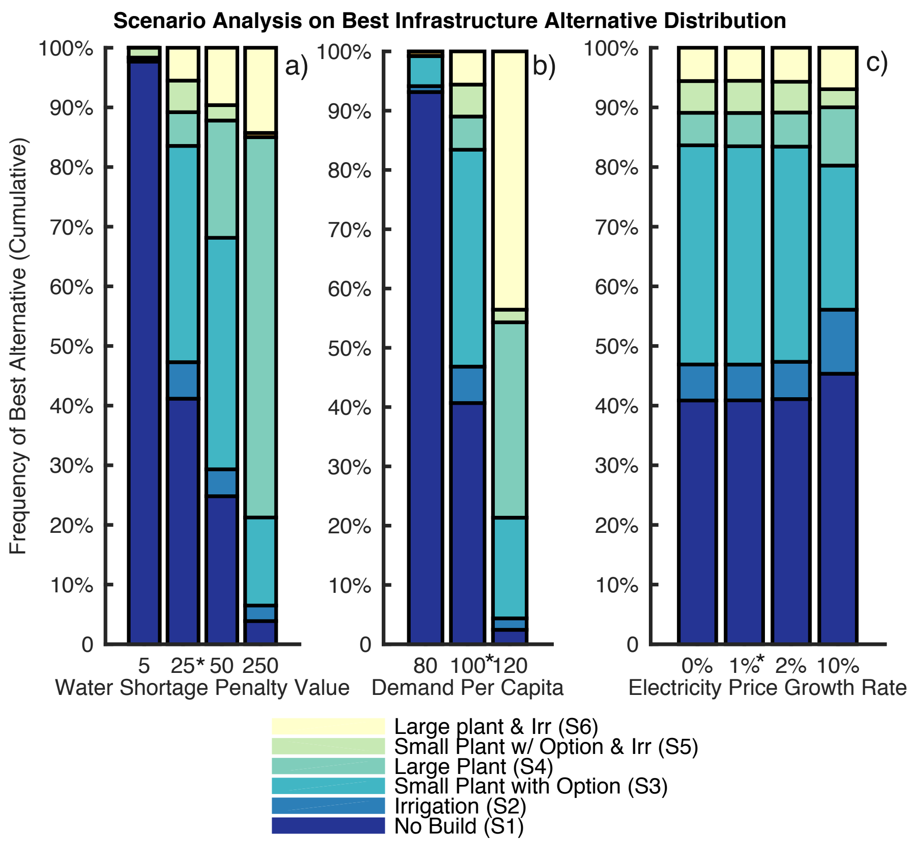

Figure 3-5: Scenario analysis on the distribution of the best infrastructure alternative chosen by the decision model across 100,000 model runs. In each model run, the best alternative is chosen based on the expected payoff. Base cases are indicated with an asterisk. In the base case, no build (S1) and small plant with option (S3) are each chosen in about 40% of runs. Results are highly sensitivity to demand per capita and the penalty value and relatively insensitive to electricity growth rate.

The results demonstrate that moderate investment increases, together with flexible infrastructure design, can mitigate water shortage risk significantly. Using a staged deployment strategy to expand if necessary when more information is available reduces shortage risk at lower cost compared to other, less flexible infrastructure options. The value of this flexibility is dependent on the nature and magnitude of uncertainties in the system. Furthermore, demand reduction strategies may reduce the need for additional capacity. These results also suggest that supply infrastructure can be regarded as an insurance policy against drought. Although the investments may be used infrequently over their lifetime, they mitigate the risk of severe economic consequences due to water shortages. This view can allow for improved risk assessment along with appropriate valuation and expectations of its utility. However, there are tradeoffs between infrastructure cost and water shortage risk.

The Victorian government's decision to build a 150 MCM/year desalination plant, one of the world's largest, has been the subject of heated debate and political backlash given the wealth of reservoir water available for years after plant came online in 2012 [126, 49]. However, as drought impacts the region again and the population continues to growth rapidly, the plant delivered its first water order in March 2017 [57], demonstrating that desalination capacity can play a role in mitigating supply and demand uncertainty even if it used infrequently.

These insights are relevant to other places facing infrastructure decisions driven by multi-year droughts. For example, several municipalities in California are considering desalination investments [54]. Although drought in California is often framed as "the new normal" because of climate change, it is important for both planners and the public to remember that high variability and extended periods of low rainfall are normal even in the absence of climate change. Using a learning-driven staged deployment approach or increasing demand reduction efforts may reduce the need for capital investment. Alternatively, framing any investments as drought insurance that may be used infrequently may increase public acceptance. This strategy was successfully employed in the UK, where Thames Water built a large desalination plant in east London in 2010 citing risks of severe water shortages [82].

Our analysis of the Melbourne case shows that much of the choice of the "best" answer is predicated not only on assumptions about the city's future but also value judgments about the value of water during times of scarcity and society's appetite for risk. The sensitivity to the penalty value suggests that working with stakeholders to choose a value that reflects society's tolerance to risk will be important in applying this method to prospective planning decisions. Future work could also incorporate economic methods to value the impacts of water shortages on society as a way to inform the choice of penalty. Modeling separate end uses — agriculture, municipal, industrial, and environmental — could be used to assess the impact of risk sharing across multiple end-use sectors. Alternatively, the water provider may invest in a water fund (at a much lower cost than committing capital for new infrastructure development) that allows the provider to subsidize costs incurred by users in years of drought. Additionally, the use of financial risk mitigation options, such as the private-public-partnership that Melbourne Water used when contracting the Wonthaggi plant, may further reduce the need for capital-intensive projects.

Future work can extend this study by incorporating additional uncertainties, and comparing the nature of key uncertainties in different regions. For example, while population growth provides significant learning opportunities for planners in Melbourne, there may be different uncertainties that drive staged deployment decisions in other regions. Future work could also explore the impact of different water conservation strategies on the necessity for water supply capacity expansion or sustainability goals and objectives [16]. Some demand reduction strategies such as fines or public education yield uncertain and variable reductions rather than the firm capacity provided by desalination. Future work could also include more detailed models of operational reservoir management to assess the impact of improved operations as an alternative to or in conjunction with infrastructure additions. Additionally, new strategies such as 'fit-for-purpose' water supply, in which water of different quality is used for applications for which the quality level is adequate [113], can be evaluated for impacts on infrastructure scale and design decisions.

Chapter 4

Managing predictive groundwater uncertainty in Riyadh, Saudi Arabia using Bayesian updating and flexible planning

This chapter has been adapted from a working paper: Sarah Fletcher, Kenneth Strzepek, Adnan Alsaati, and Olivier de Weck, "Managing Predictive Groundwater Uncertainty in Riyadh, Saudi Arabia using Bayesian updating and Flexible Design", 2018.

Abstract: Water supply infrastructure planning in groundwater-dependent regions requires predictions of the impact of pumping on the groundwater system in order to ensure that withdrawals can be used to reliably and sustainably meet demand. However, groundwater models often have high predictive uncertainty due to the heterogeneity of groundwater aquifers in combination with typically limited data availability. Previous work has assessed the impact of uncertainty in aquifer hydraulic conductivity (K) and storativity (S) on hydraulic head predictions and the potential for new head observations to reduce uncertainty. Here we extend this work to assess the impact of additional head observations not only on predictive uncertainty but also on infrastructure planning from a systems perspective. Further, we assess the potential for flexible infrastructure planning to manage predictive groundwater uncertainty. To do this, we develop an integrated modeling approach that uses Bayesian inference on a groundwater model to characterize a multi-stage stochastic program.

An artificial neural network serves as a statistical surrogate of a numerical groundwater in order to make the problem computationally tractable. This allows us to derive and assess flexible planning strategies using engineering options analysis. We apply this approach to a desalination planning case in 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 has large value in mitigating the risk of over-building infrastructure with minimal reliability risk.

4.1 Introduction

Water planners face the challenge of developing policies, infrastructure, and management strategies to ensure that high-quality reliable water supply is available to meet societal demand in the future. This requires predictions about future water availability and demand. However, predictions face uncertainty due to limited information to characterize water systems today and how they will evolve in the future. Groundwater resources in particular often face substantial predictive uncertainty. The high degree of spatial heterogeneity in groundwater aquifers combined with data limitations often makes it difficult to accurately estimate key parameters such as hydraulic conductivity. However, filling in knowledge gaps with additional observations can reduce predictive uncertainty [31, 117]. This in turn enables more reliable and efficient planning. Therefore, if poor aquifer characterization makes it difficult to know when current withdrawals will become unsustainable, a flexible infrastructure development plan that can adapt as more information is collected may maintain reliable, sustainable water supply without over investment.

Assessing uncertainty in hydrological modeling, and in groundwater in particular, has a long history [40]. Recently, much attention has been paid to the value of the calibration process in reducing predictive uncertainty in groundwater modeling [111]. Bayesian calibration methods, in which observations are used to update a prior distribution of parameters, are increasingly applied to groundwater inverse problems. Approaches can use either formal likelihood methods [100] or a generalized likelihood uncertainty estimation approach, which takes a broader view of the likelihood function that incorporates analyst judgment [15]. Prior work has also assessed the value of new data in reducing predictive uncertainty. Targeted investment in specific types of data, strategic locations of data, or additional volume of data and incorporating it into the calibration process can reduce predictive uncertainty [31, 50, 117, 173]. Bayesian calibration is typically computationally expensive due to the need to use Monte Carlo approaches to numerically calculate the posterior; however, algorithmic advances and approximate approaches are reducing this barrier [21]. Kalman filters, a form of recursive Bayesian inference, have been applied in groundwater applications such as hydraulic head prediction using multiple conceptual models [172] and joint inference of head and recharge [46].

Recent work has also highlighted the importance of predictive uncertainty in groundwater management decisions [36]. Groundwater management models typically combine a simulation model, such as a numerical groundwater model, with an optimization model; a wide variety of techniques exist [125]. Stochastic and robust optimization methods for incorporating uncertainty into groundwater management models have existed since the 1980s [160]. However, embedding a groundwater simulation model into an optimization model is computationally expensive; the optimization may require many thousands or millions of calls of a simulation model that is already time consuming. Past approaches have used simplified groundwater simulation models, such as a response matrix/unit impulse approach [71, 160], analytical models [120], or statistical surrogate models [9]. Only a limited number of groundwater management models use a multistage stochastic decision approach, in which a decision in an early stage must be made in the face of uncertainty that will be realized in a later stage. Two-stage stochastic linear programming models typically use a simple groundwater planning formulation and/or an inexact solution approach [76, 81].

Multistage stochastic optimization models are powerful, despite their computational expense. These models, such as stochastic dynamic programming SDP, allow the user to identify an optimal action for each possible state of the system, accounting for uncertainty across all possible future states. Non-stationary formulations can be used to represent how uncertainty can change over time. These approaches are therefore widely used in other domains in the evaluation of flexible infrastructure planning, in which infrastructure is designed to be able to change in the future [167]. The performance of flexible planning strategies can be be evaluated using engineering options analysis (EOA), in which simulation models are used to evaluate the tradeoffs between flexible and static approaches [33]. Fletcher et al. (2017) [51] use decision analysis to evaluate flexible desalination plant design for drought resilience in the face of both uncertain runoff and demand growth. EOA has also been applied to water distribution network design [101], and adapting water supply systems to climate change [53]. Multi-stage flexible pumping strategies for groundwater remediation have been developed using dynamic programming and other multistage optimization approaches [124, 139, 29].

This study applies a multistage stochastic optimization model to water supply infrastructure planning under predictive groundwater uncertainty. We combine SDP with Bayesian inference to develop a planning model that assesses the potential for future observations to reduce uncertainty over time. Additional groundwater data can not only reduce uncertainty in the predictions from a groundwater model, but also mitigate the uncertainty impacting groundwater management decisions. We therefore link potential reductions in predictive uncertainty to a planning model that evaluates new water supply infrastructure alternatives. This demonstrates the value of additional information in both predictive power and in key planning metrics like reliability and cost. Finally, we use the planning model to develop flexible infrastructure strategies and use EOA to assess their potential to mitigate risk. As uncertainty is updated over time using the Bayesian inference approach, flexible options can be exercised in response. Our approach addresses computational constraints by training an artificial neural network (ANN) on a numerical groundwater model to serve as a statistical surrogate model that can be efficiently embedded in an SDP.

We apply this approach to a case from Riyadh, Saudi Arabia where non-renewable fossil aquifers comprise half of the city's water supply. Large withdrawals from these aquifers over the past 30 years have led to substantial decline in hydraulic head; eventually, maintaining current withdrawal rates with existing pumping infrastructure will no longer be possible. However, these aquifers are poorly characterized, leading to substantial uncertainty in how quickly hydraulic head will decline and therefore when a transition to alternative supply will be necessary. As Riyadh considers expensive investments in desalination and new groundwater development to replace current groundwater supply, 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.

The remainder of this paper is organized as follows. Section 4.2 presents the method in a generalized form. Section 4.3 applies this method to a case from Riyadh, Saudi Arabia, and Section 4.4 presents results. Section 4.5 concludes with summary and discussion.

4.2 Modeling approach

The primary contribution of this paper is to integrate existing tools to develop a method to assess the value of groundwater information and the value of adaptive, flexible planning in mitigating the risk of predictive uncertainty in groundwater management. We use Bayesian inference with a numerical groundwater model to update prior distributions of key aquifer parameters and therefore predictions about head in the future. These predictions are embedded in a SDP where each state of the model in future time periods serves as a potential hypothetical future observation. The SDP model is then used to evaluate flexible planning options, which are evaluated using EOA.

This method is implemented using the following steps, illustrated in Figure 4-1:

1. Use a groundwater model to characterize predictive uncertainty in hydraulic head. This generates a prior distribution for hydraulic head over time that reflects the best available information at the beginning of the planning period.

2. Apply Bayes' theorem to develop posterior distributions for hydraulic head that update uncertainty to reflect possible future observations. The state space of the SDP comprises possible future values of hydraulic head. Each state value is applied as an observation in Bayes' theorem to assess how our understanding of uncertainty will change if that future state of hydraulic head is reached. A surrogate model, in which an ANN is trained on the groundwater model output, is used to enable efficient numerical integration to calculate the posteriors.

3. Develop a multistage SDP in which the transition probabilities (the probability of going from a certain head level in time t to a different head in time t+1) are characterized using the posterior distributions from step 2. Use the SDP results to develop flexible water infrastructure strategies that take into account the potential to learn in the future.

4. Evaluate flexible infrastructure strategies and compare to traditional static planning approaches using EOA.

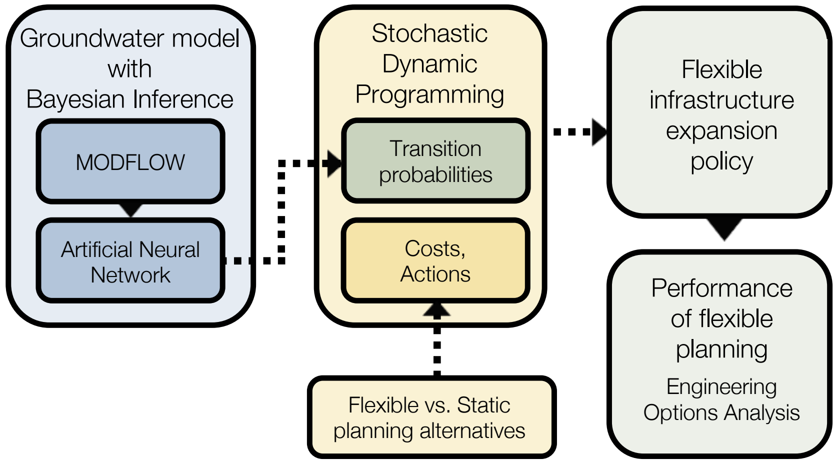

Figure 4-1: Schematic of method used to develop and evaluate flexible infrastructure expansion policies that account for the potential to learn about uncertainty over time. The method integrates a numerical groundwater model and its ANN-based statistical surrogate into a multi-stage stochastic dynamic 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.

Characterizing predictive uncertainty using a groundwater model

A groundwater simulation model is used to predict hydraulic head h in the future as a function of an uncertain input parameter vector θ. In our application, h is the hydraulic head in a single representative well, and θ comprises the K and S of a confined aquifer. We use the finite difference groundwater model MODFLOW [65]. This model can be interpreted as an operator g mapping parameter values θ to predicted state variable values h.

$$h(t) = g[\theta, t] + \epsilon \tag{4.1}$$

Predictive uncertainty arises from uncertainty in the model parameters θ and the measurement ϵ error. A prior parameter distribution $p(\theta)$ and error distribution $p(\epsilon)$ is developed. In our application where historical head data is limited, we use parameter estimates from a government hydrogeological study to characterize $p(\theta)$ and assume a normal error distribution with variance of 5m; future applications could use Bayesian calibration approaches. We assume that the pumping rate is fixed over time.

Because our approach requires numerical calculation of many posterior distributions using the groundwater model, we develop a surrogate model g' that captures the key dynamics of g with greater computational efficiency. Our application uses an ANN, trained on 400 runs of the MODFLOW model with a variety of parameter inputs. This provides an instantaneous mapping from any realization of θ to the corresponding value of $h(t)$. This surrogate approach, rather than an analytical alternative like a response matrix, enables generalization to unconfined nonlinear groundwater models in future applications.

Monte Carlo simulation is used to sample from $p(\theta)$ and $p(\epsilon)$, and run a forward simulation of head over time for each sample. We use this simulations to develop a 99% confidence interval for head over time; this is used as the feasible range in the SDP. This feasible range is then discretized to create $h_{dis}(t)$. The values in the set $h_{dis}(t)$ will serve as potential hypothetical future observations in the Bayesian inference. The discretization granularity should be informed by the range of the set and the SDP formulation; our application uses 1m resolution in hydraulic head.

Bayesian inference to characterize SDP transition probabilities

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 $p(h(t+1)\,|\,h(t), a(t))$ 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 describe the probability distribution of drawdown in head in the next time period given the head today and pumping rate. By using non-stationary transition probabilities, in which the distribution for head in the next time period can change over time, we take into account the potential to learn about predictive uncertainty in the future.

The transition probabilities are characterized using Bayesian inference. $p(\theta)$ 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 $p(o\,|\,\theta)$ is characterized using equation 4.1.

$$
\begin{gathered}
p(\theta \mid o) = p(o \mid \theta) * p(\theta)/p(o) \\
o \in h_{dis}(t)
\end{gathered}
\tag{4.2}
$$

Because no analytical form of the posterior exists, numerical integration is used to estimate the posterior; Markov chain Monte Carlo (MCMC) methods could also be applied.

Deriving and evaluating flexible groundwater management strategies

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

$$
V(s,t) = \underset{a \in A}{\operatorname{argmin}} \; C(s(t), a(t), t) \; + \; \gamma \sum_{s \in S} p(s(t+1) \mid s(t), a(t)) \; * \; V(t+1, s(t+1)) \tag{4.3}
$$

where $V(s,t)$ is the optimal action for state s at time t, C is the cost 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 planning or management decisions undertaken by the water planner. They could include pumping volumes, demand management policies, and building new infrastructure. Costs are a function of the current state, time period, and action; they can include capital and operating costs of infrastructure as well as penalties for failing to meet demand or other performance metrics. The sum in the above formulation calculates the expected future cost; this can be extended to other decision criteria. For example, a risk averse planner may prefer to minimize the 5th percentile of future cost.

Flexibility in groundwater management can take many forms. Adaptive pumping policies can enable the resilience of groundwater resources by limiting withdrawals when aquifers are most vulnerable. Demand reduction policies can be triggered during times of scarcity. Infrastructure can be designed to change operations or expand capacity when needed. In our application, we focus on flexible infrastructure planning, in which the development of new infrastructure is conditional on the future state of the groundwater system. Planners can make design and siting decisions upfront, enabling timely development in the future if needed. In this method, flexibility is evaluated through the use of an action space that varies as a function of the state of the system and time. This enables modeling of the management or planning policies described above that are dependent on, for example, the level of hydraulic head and water demand.

The key value of using a multi-stage stochastic programming approach in combination with Bayesian inference, as opposed to deterministic or robust optimization approaches, is that it explicitly allows for assessing how uncertainty can change over time as new information is collected and develop strategies that can anticipate this change in advance.

4.3 Application to Minjur aquifer in Riyadh, Saudi Arabia

The region of Riyadh had a population of 7.7 million in 2014 up from 5.5 million in 2004. [143]. Growing at an average of 3.5 % a year between 2004 and 2014 [143], Riyadh is both the most populous and fastest growing region in Saudi Arabia. Demand per capita including losses is currently about 300 liters per person per day (l/p/d), totaling an average of 1.86 MCM/d supplied in 2016 [6]. A highly arid region, receiving on average only 24 millimeters (mm) of rainfall per year [30], Riyadh's water needs are supplied by seawater desalination piped from the Arabian Gulf and groundwater extraction. In 2016, desalination supplied an average of 1.4 million cubic meters per day (MCM/d) of water to Riyadh and groundwater supplied 1.07 MCM/d, over 90% of which came from deep fossil aquifers [30]. The Minjur aquifer comprises the largest share of these aquifers, supplying about 300,000 cubic meters per day (m^3/d).

The Minjur aquifer, which is the focus of our study, has faced substantial drawdown of hydraulic head due to the combination of large withdrawals and minimal recharge. The government has announced plans to promote efficient water use using tariff reform and reduce leakage in the distribution system, aiming to reduce net demand per capita to 170 l/p/d by 2030 [6]. Additional desalination capacity serving Riyadh is planned to be added in the next few years. About 370,000 m^3/d of treated wastewater is currently reused in agriculture, landscape irrigation, and industrial applications, with goals to increase wastewater reuse in additional applications. [30]. However, Riyadh's water supply plans assume continued withdrawals from the Minjur at the current rate, or perhaps adding additional groundwater development. As the aquifer continues to drawdown, the current rate of withdrawals will eventually become uneconomical, even with substantial subsidies, or technically infeasible for existing pumping infrastructure.

A key challenge in planning for depletion of the aquifer is the substantial uncertainty in predicting how quickly hydraulic head in the aquifer will drawdown, even if pumping rates remain constant. Estimates for K and S range from 1.39×10^{-5} m/s to 5.31×10^{-4} m/s and 1.00×10^{-4} to 1.12×10^{-3} respectively [41]. Calibrating a numerical groundwater model to more precisely characterize the transmissivity and storativity of the Minjur in the Riyadh region, as well as the spatial heterogeneity of those parameters, requires large volumes of water monitoring data. In Riyadh as in many regions, this type of data is limited.

We apply our planning framework with uncertainty updating to assess 1) how predictive uncertainty in aquifer depletion rates can be updated over time and 2) how flexible, adaptive infrastructure planning can be used to mitigate risk from this uncertainty. In particular, we model the development of new desalination infrastructure to replace withdrawals from the Minjur. We contrast 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 infrastructure with a flexible approach. In the flexible approach, planners observe hydraulic head over time and decide if and when to build additional capacity based on updated depletion prediction. To facilitate this approach, planners take advance preparations in the form of design, siting, permitting, initial contracting, etc. so that infrastructure can be developed quickly to avoid reliability outages if and when it becomes clear that it is needed.

Groundwater model

The Minjur is a Triassic aquifer composed primarily of sandstone and shale, extending over 800 km across the central Arabian peninsula. There is an outcrop area approximately 100 km west of Riyadh. The aquifer is estimated to be 315 m thick in the Riyadh area. Recharge in the outcrop area is small, estimated between 3 and 25 mm per year [5, 169].

We model the Minjur aquifer in the Riyadh area using the numerical groundwater modeling software MODFLOW [65]. The model is based on that of [169], which is a study by the United States Geological Survey (USGS) that was used in the Saudi government's 1984 Water Atlas [109]. While numerical groundwater modeling techniques have progressed substantially since the 1980s, the USGS report is the most recent publicly available study of the Minjur, and it provides a simple model appropriate for demonstrating our framework. Following the USGS study, we use a 423 kilometer (km) by 288 km two-dimensional rectangular grid with 315 meter (m) thickness. The lower left corner of the grid is positioned at latitude 22.5° and longitude 45.79°, putting Riyadh and the major pumping well fields in the center of the study area. The left side of the grid is bounded by an irregular no-flow boundary representing the outcrop of the aquifer. The rest of the grid is also bounded by no-flow boundaries; these boundaries are far enough away that they have negligible impact on the main study area in and surrounding Riyadh. The grid cells are 1 km x 1 km in the main study area and gradually increases to as large as 15 km. While the large grid spacing may underestimate drawdown in individual wells, it allows us to keep the computational cost of the model small and is appropriate for assessing long-term regional impacts on head [8]. The study area, including groundwater pumping and desalination infrastructure, and a sample simulation of the groundwater model are shown in 4-2. A hydrostratigraphic cross section is shown in Figure 4-3.

To characterize the predictive uncertainty in head, we fit prior densities for K and S using the ranges described above; K is assumed lognormal and S uniform. Because of data limitations and for simplicity, we assume these parameters are uncorrelated and homogeneous throughout the aquifer and do not calibrate to monitoring targets. Future work could include MCMC [68, 98] or null-space Monte Carlo [159] methods to generate random fields of parameters consistent with calibration targets.

We model the impact of 120 pumping wells in the Riyadh area. The locations and historical pumping rates of these wells are provided in [169]. We have 2010 data on 60 of these wells which account for over 80% of the withdrawals. The starting head is between 200 and 250 meters below land surface (m.b.l.s.), the range reflects a substantial cone of depression around Riyadh. Recharge is assumed to be 5 mm/y in the outcrop area. We use a transient model with a 30-year simulation horizon and weekly time steps.

In order to develop a fast, statistical surrogate model that can be efficiently embedded in the SDP model, we train an ANN on the output of the MODFLOW model. Latin hypercube sampling is used on the prior parameter distributions to generate 400 K and S samples as input to the MODFLOW model, yielding 400 output time series of hydraulic head. Pre- and post-processing was completed using the Python library FloPy (Bakker et al., 2016). One representative well, chosen from the largest well field in the center of Riyadh, is used to represent head decline in the planning model. We therefore train the ANN to predict the 30-year time series in that well, using K and S as inputs. MATLAB is used to train a 2-layer feed forward network; the RMSE is about 1 m. Details on the ANN architecture and skill are provided in Appendix B.

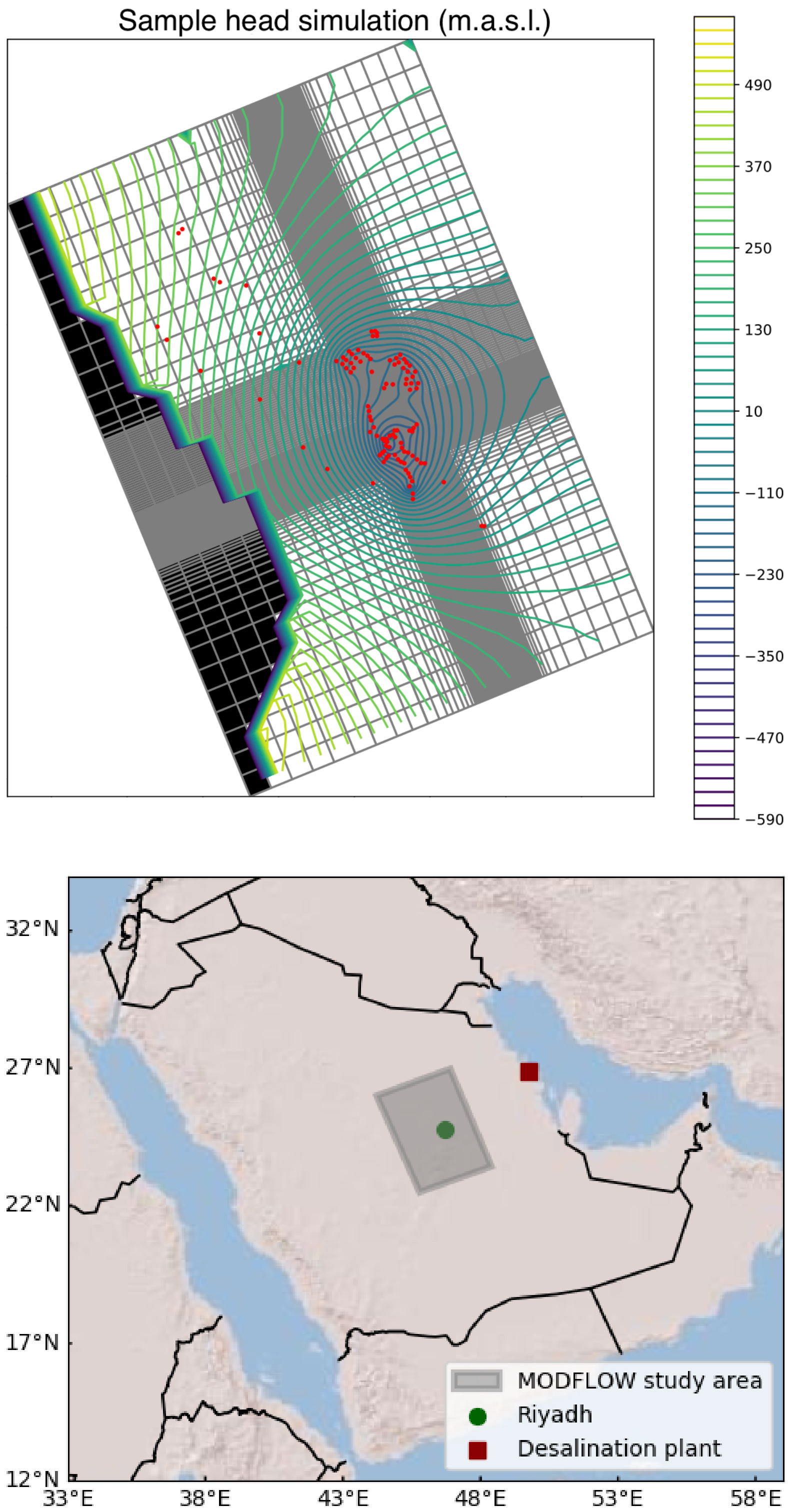

Figure 4-2: Top: Schematic of MODFLOW grid with hydraulic head contours from one sample simulation. Pumping wells shown with red dots. Outcrop area colored black on left side of grid. Bottom: Study area with grid location, Riyadh city center, and location of proposed desalination plant in Jubail.

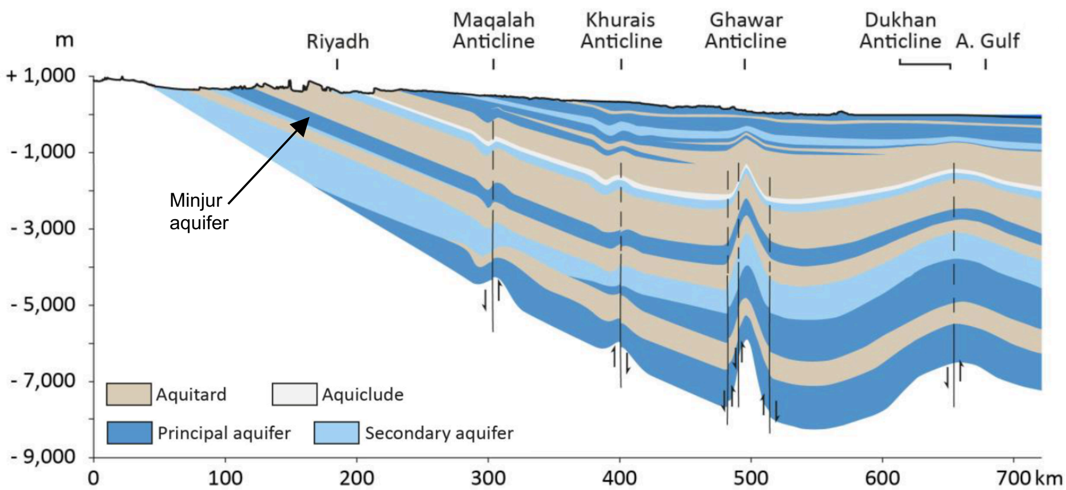

Figure 4-3: Hydrostratigraphic cross section of study area including Minjur aquifer. Reproduced and edited with permission from [41]

Planning Model

We formulate a planning model that represents a simplified version of the planning challenges described above but captures the key dynamics of the uncertainty in head decline. We use the head in a single well as a proxy for hydraulic head decline; we choose a well in the Salbulk well field, which comprises the largest share of withdrawals from the Minjur, close to the center of the cone of depression around Riyadh. 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.b.l.s.. Therefore, we impose a drawdown limit of 50 m; beyond this limit pumping is infeasible, and planners must either supply water from new sources or incur penalties for unmet demand. We consider one representative new infrastructure alternative: a desalination plant with 108 MCM/y of capacity, sized to replace all withdrawals from the Minjur aquifer. The Bellman equation in 4.3 is therefore parameterized as follows in Equation 4.4:

$$
\begin{aligned}
S &= \{h_t, x_t\} \\
A &= \{p_t, e_t(x_t)\} \\
C_t &= P(h) * p_t + E * e_t + O * x_t * e_t + S * \max(0, D - x_t)
\end{aligned}
\tag{4.4}
$$

where

- t = time step in the model in years between 1 and 30
- h_t = hydraulic head (meters) in representative well at time t
- x_t = desalination capacity (MCM/y) at time t. x_t starts at 0 and changes to 108 two years after the expansion option is exercised if at all.
- $p_t \in \{0, 1\}$ where 0 and 1 indicate respectively that pumping is off or on at time t
- $e_t(x_t) =\in \{0, 1\}$ where 0 and 1 indicate respectively that infrastructure option i is not expanded or expanded. If $x_t = 108$, indicating that the desalination plant has already been added, then e_t is constrained to equal 0.
- $P(h)$ = Marginal cost of pumped groundwater at hydraulic head h (USD/MCM)
- E= Infrastructure expansion cost (USD)
- O= Desalination marginal cost (USD/MCM)
- S = Shortage cost (USD/MCM) reflecting damages that are incurred if the depth limit is reached before adding desalination infrastructure, and
- D = Demand (MCM/y), assumed to be 108 equivalent to estimates for current withdrawal rates from the Minjur.

Details of the cost assumptions using in the formulation can be found in Appendix B.

The transition probabilities for the individual state variables are assumed to be independent. The transition probabilities for hydraulic head are determined by the groundwater model and Bayes' theorem as described in equations 4.1 and 4.2. The transition for the capacity state is deterministic, determined by the expansion action e_t. We assume the desalination capacity is available two years after the decision to expand. This reflects the flexible planning process described in the previous section in which upfront planning enables timely capacity additions.

4.4 Results

We now present results from the application of the method to the case in Riyadh. 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 derive the optimal capacity expansion policy under uncertainty. Finally, we use the optimal expansion policy to simulate the performance of the flexible approach in comparison to two static alternatives.

Groundwater Bayesian learning

We generate a confidence interval for hydraulic head predictions in our representative pumping well using Monte Carlo simulation: we sample many realizations of K and S from $p(\theta)$ and apply the ANN groundwater model g'. The initial predictive uncertainty is quite large due to the substantial uncertainty in both K and S — more than an order of magnitude for each parameter. A 90% confidence interval shows that hydraulic head in the well if current pumping rates continue could range between 305 meters above sea level (m.a.s.l.) and 245 m.a.s.l., based on a starting head of 337 m.a.s.l. The drawdown limit beyond which the current pumping infrastructure is no longer able to withdraw water is at 287 m.a.s.l. Therefore, at he beginning of the planning period, there is substantial uncertainty about whether this limit will be reached over 30 years.

However, the application of Bayes' theorem to new observations enables substantial reduction of this uncertainty. This is shown in Figure 4-4. On the right side, samples from the $p(\theta)$ are shown; the corresponding confidence intervals are at left. At each time step, a new hypothetical observation o is sampled from within the existing confidence interval for that time period. This hypothetical observation is used to update $p(\theta)$ to get $p(\theta|o)$. In the next period, a new set of samples is drawn from $p(\theta|o)$ and used to simulate a new confidence interval for hydraulic head. The updating process is done on a yearly time step; however, the results are shown bi-yearly in figure 4-4 for visual clarity. Different color shades are used to distinguish time steps; the darkest red samples correspond to the last time step. These dark red samples span a reduced subset of the original parameter space, showing that the model is able to infer which possible combinations of K and S could have led to the simulated observations.

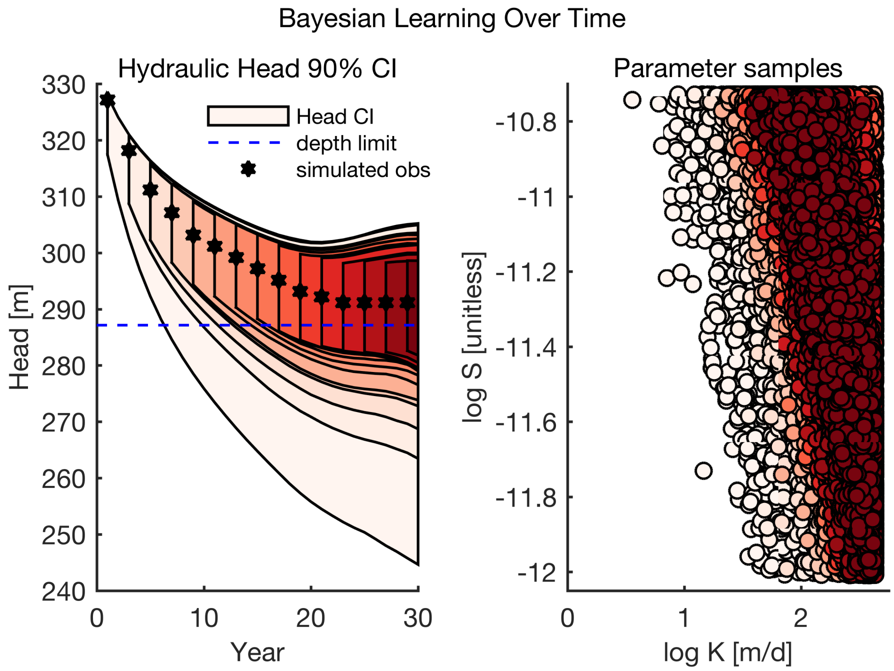

Figure 4-4: A single simulated time series of hydraulic head observations are used to update the parameter distribution (right) and therefore the distribution for projected head (left). The darker red colors highlighting a subset of samples in the prior parameter space indicate the ability of the simulated 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. The large reduction in the confidence interval indicates high value of information; however, the value of information faces diminishing returns with additional observations.

This result shows the high value of information in reducing predictive uncertainty. By year 10, the 90% confidence interval has been reduced by half. These early observations have large value because the uncertainty at the outset was so large. Between years 10 and years 20, the confidence interval continues to narrow but at a much slower rate. The value of these observations faces diminishing marginal returns over time as the uncertainty is reduced. Note that this plot shows one possible simulated set of observations in which the final hydraulic head does not reach the drawdown limit. A different simulation may, for example, show a more rapid depletion rate of the aquifer in which the confidence intervals instead narrow at the bottom half of the original confidence interval. 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 predictive uncertainty.

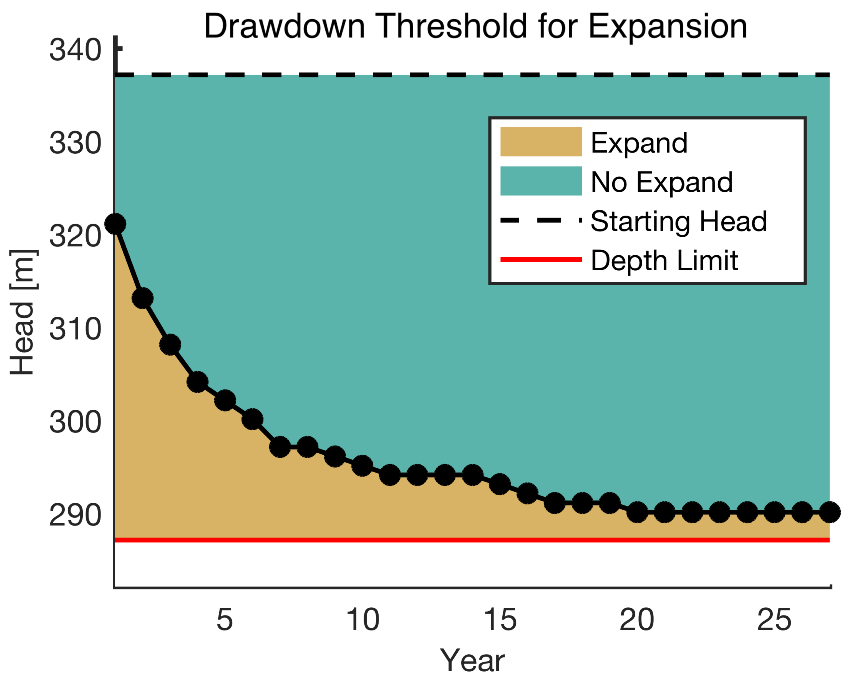

Figure 4-5: The SDP results provide a hydraulic head threshold beyond which expanding desalination capacity is optimal. The threshold is above the depth limit so that desalination capacity can come online after two years without incurring shortage damages in the interim. This threshold approaches the 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.

SDP

As described in the previous section, a single simulated set of hypothetical future observations reduces the predictive uncertainty in the groundwater model over time. The SDP models all the possible hypothetical future observations probabilistically through the use of the transition probabilities. The hypothetical observations correspond to possible hydraulic head states in the SDP state space. The optimal expansion policy in time period t, therefore, describes the best decision given the remaining uncertainty that exists after the information based on the current hydraulic head state is used to update the future uncertainty. It is a function of both the hydraulic head and time.

Figure 4-5 shows the drawdown threshold for the decision to add desalination capacity. Beyond this threshold, the optimal policy is to add desalination capacity if none has already been added. If the threshold has not been reached in a particular time step, the optimal policy is to not add new capacity. As seen in the figure, 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 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. Observing a hydraulic head of 300 m in year 15, however, indicates a much slower drawdown rate. Therefore, the optimal expansion threshold is closer to the drawdown limit because the risk of rapid head decline in the two years it would take the desalination plant to come online is much lower.

Engineering options analysis

Next, 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 4-6 shows the distribution of capacity expansion decisions across the 1000 simulations. As indicated by the black bar at the right of the plot, desalination capacity is never added in just under half of the simulations. In these simulations, the drawdown of hydraulic head is slow, never crossing the drawdown expansion threshold. However, in over half 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 models is more similar; if we have not learned enough to make the expansion decision before year 15, we are unlikely to learn enough in years 15-17 to make that decision either. Finally, the frequency of expansion tapers off around year 21. This is because of the planning formulation; when the desalination plant is brought online late in the planning period, it only provides value for a small number of years. Therefore, it is often optimal to incur shortage damages for a short time instead. This is a known limitation of finite-horizon

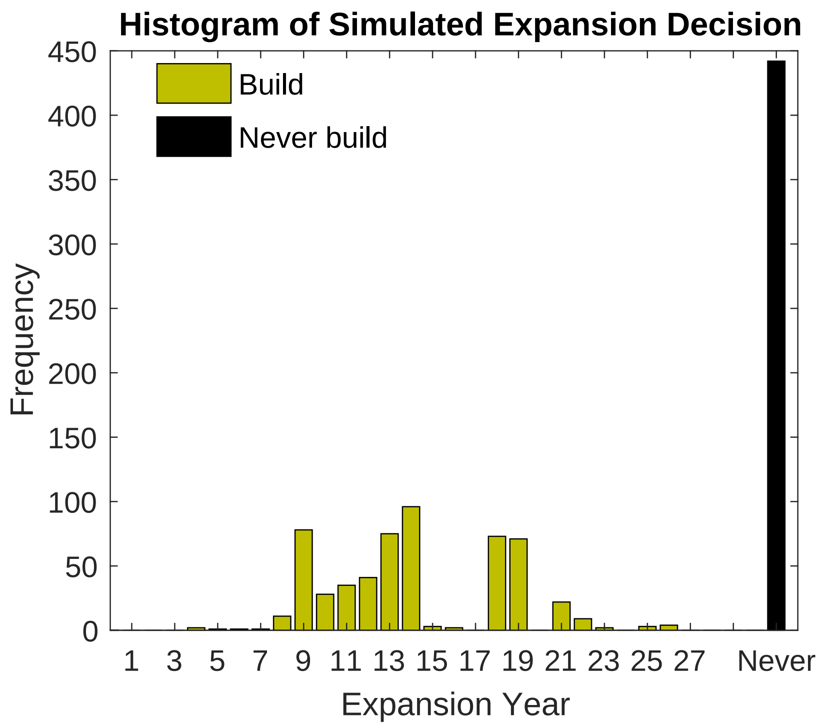

Figure 4-6: Histogram showing whether and when desalination capacity is added across 1000 forward simulations. The desalination plant is added in a little under half of simulations. When desalination capacity is added, the timing of that decision variables considerably. This variation is driven primarily 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.

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. The late-period results should therefore not guide planning decisions.

Finally, the performance of this flexible strategy across 1000 simulations is compared to the two static alternatives: one in which the desalination plant is built at the start of the planning period, and one in which the desalination plant is never built. Figure 4-7 presents cumulative distribution functions (CDF) of the total cost C over the 30-year planning period for each of the three planning alternatives. As described in the previous section, this cost includes capital and operating costs for the desalination plant, groundwater pumping costs, and damages for any water shortages incurred. The static no-build alternative, shown in orange, incurs only pumping costs in about 50% of simulations; this is shown by the vertical section of the CDF in the lower half of the plot. In the upper half of the plot, however, we see that the no-build alternative incurs substantial shortages in more than half of simulations. The static build alternative is a little over half a billion dollars more expensive than the no-build alternative in the 50% of simulations when shortages are not incurred; this is seen in the bottom half of the plot. This difference reflects the capital cost of the desalination plant and demonstrates that the static build alternative faces substantial over-build risk. In the upper half of the plot, however, we see that the presence of the desalination plant eliminates the risk of water shortages; the modest cost increases in the blue line here reflect increasing pumping costs and the presence of desalination operating costs.

The flexible alternative mitigates both the over-build risk faced by the static build alternative and the reliability risk faced by the static no-build alternative. In the top half of the plot, the yellow line representing the flexible alternative nearly overlaps the blue line. This shows that it eliminates nearly all the shortage damages. Small deviations to the right of the blue line show small shortages that are incurred either by bringing the desalination plant online slightly too late or by not building at the end of the planning period. In the bottom half of the plot, we see that the flexible alternative overlaps the static no-build option in about 40% of simulations, indicating its ability to prevent over-building. In the 10% of simulations between the 40th and 50th percentiles approximately, the flexible alternative does over build; it is aligned with the more expensive build option rather than the less expensive no-build option. Because of this and the small deviations at the top of the plot, the flexible alternative does not completely stochastically dominate the other two alternatives.

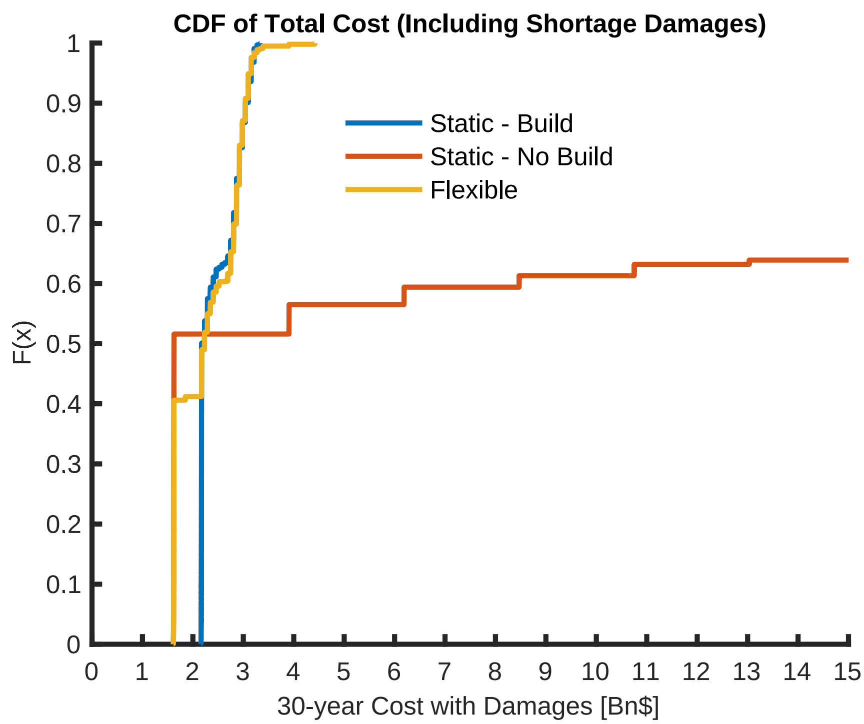

Figure 4-7: CDF of total cost by infrastructure alternative. Costs include capital and operating cost of desalination infrastructure, groundwater pumping costs, and damages for water shortages. The flexible planning alternative mitigates almost all the reliability risk in comparison to static no-build alternative. It also prevents overbuilding in comparison to the static build alternative in about 80% of simulations. The flexible alternative saves an expected $200 million and mitigates both upside and downside risk substantially, demonstrating high value of flexibility. Horizontal axis truncated for visual clarity; no-build costs increase to a maximum value of $45 billion

However, it clearly eliminates most of both the upside and downside risk. The advantages of the static alternatives are limited. Further, its expected cost of \$2.28 billion is modestly lower than the \$2.47 billion of the build alternative and substantially lower than the \$13.23 billion of the no build static alternatives respectively. The value of flexibility, therefore, is high.

Sensitivity Analysis

These results rest on a number of assumptions made in the groundwater model and planning formulation. Two assumptions that often strongly influence the results in infrastructure planning problems are the discount rate and the value of reliability, which is formulated here as a cost imposed on any water shortages that are incurred. In the results presented previously we 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. Here we assess the impact of adding a 5% discount rate. The previous results also assumed a shortage cost of \$20/m^3, based on World Bank estimates of water productivity in Saudi Arabia. [158]. We now present results varying this shortage cost to be \$5/m^{3}and \$50/m^3.

Figure 4-8 again presents CDFs of the total cost of the three planning alternatives across 1000 simulations as Figure 4-7 did; now, scenarios for a 5% discount rate, \$5/m^3 shortage cost and \$50/m^3 shortage cost are shown. These plots show that while the precise performance of each of the alternatives varies across scenarios, the high value of flexibility does not. 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. When a 5% annual discount rate is added, the flexible alternative performs even better than before. It almost completely stochastically dominates the other two, with the exception of about 5% of simulations around the 50th percentile where it overbuilds. The only significant impact of the high shortage cost is to make the no-build alternative perform substantially worse. The horizontal axis is truncated for visual clarity; the 90th percentile costs reach 82 \$ billion. The lower shortage cost improves the performance of the flexible alternative by decreasing the frequency of overbuilding. Thus we conclude that high value of flexibility with few trade-offs in comparison to the static alternatives is robust to changes in discount rate and shortage cost, both of which often impact the value of flexibility substantially.

4.5 Discussion

Our results highlight both the value of information and the value of flexibility in reducing and managing predictive groundwater uncertainty. The application in Riyadh, Saudi Arabia assesses a planning problem in which alternative supply sources, in this case desalination, must be developed in response to aquifer depletion. A traditional planning approach would use the best hydrogeological studies available — or commission an expensive new study — to make predictions about future water availability, and make plans to develop alternative sources in the future based on the best prediction today. Even our best predictions, however, are subject to uncertainty. Fully characterizing the transmissivity and storativity of an aquifer requires a large amount of data that is often not available, especially in the developing world. Characterizing this uncertainty and making plans that explicitly acknowledge the possibility of unexpected outcomes can enable plans that are robust to a wider range of futures.

However, while it is important to account for uncertainty in planning, it is also important to asses the extent to which that uncertainty can be reduced in the future with new information. Bayesian calibration methods have enabled probabilistic characterization of predictive groundwater uncertainty and demonstrated the value of additional data in reducing that uncertainty. In this study, we build on these approaches by connecting predictive uncertainty to planning decisions. We assess the value of information not only in reducing predictive uncertainty, but also in enabling effective planning under uncertainty. Further, we show that flexibility, when combined with uncertainty reductions over time, can enable reliable planning decisions at reduced cost compared to static, robust approaches. In this case, we found the high value of flexibility to be robust to variations in the cost of water shortages, or how much value society places on water reliability.

We achieve this by developing a new planning framework that combines Bayesian inference on a high-fidelity groundwater model with multi-stage stochastic programming; this is made computationally tractable through the use of a ANN-based statistical surrogate model. This optimization approach enables planners to develop strategies that explicitly account for the range of uncertainty in the future and to choose different, adaptive actions

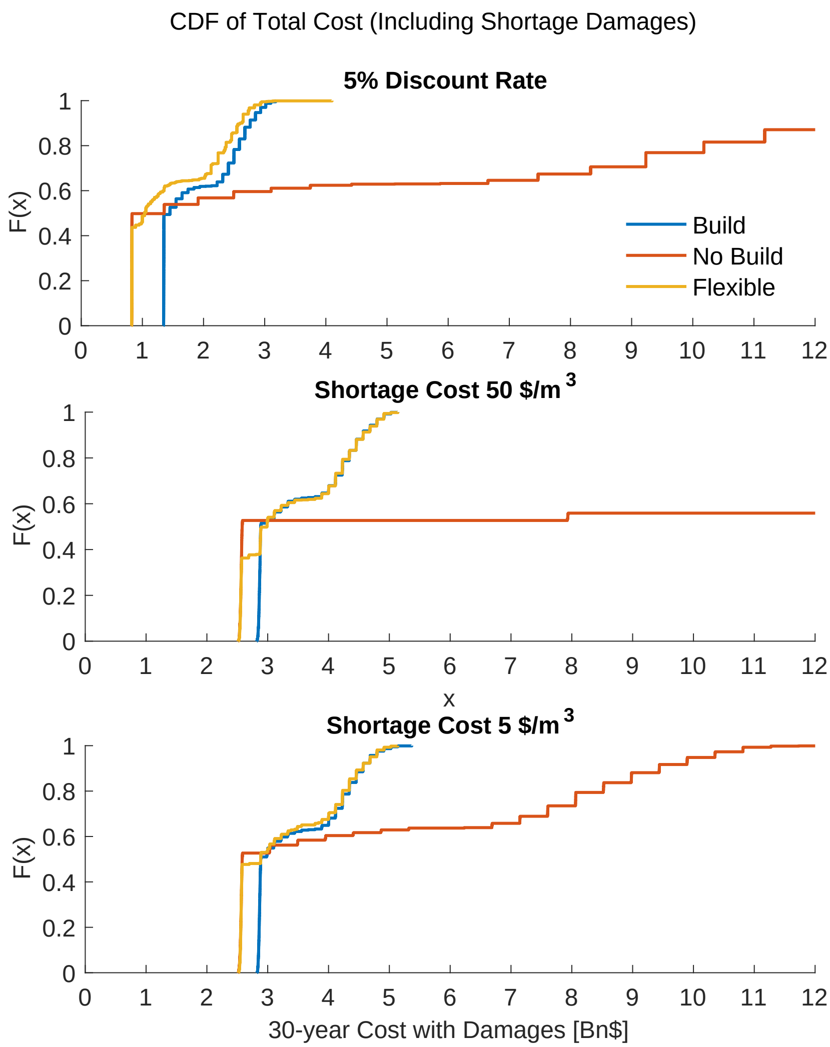

Figure 4-8: Sensitivity analysis

as the state of the system evolves over time. Uncertainty is characterized using transition probabilities, which describe the probability distribution for the state of the system in the next time period given the state today. Our approach characterizes these transition probabilities using Bayesian inference on a groundwater model, allowing us to model the potential for a certain hypothetical future observation to update the uncertainty. We can infer, for example, that observing only 10 m of drawdown in hydraulic head after 20 years means that we must have relatively high K and storativity and therefore that low drawdown will likely continue in the future. Including this potential future information — across all the possible observations we might encounter — enables adaptive strategies that account for the fact that we can learn in the future.

Each of the individual components in this analysis – MODFLOW, ANNs, SDP, Bayesian inference — is a well established existing method. The methodological contribution here lies in a novel framework that integrates them in a novel way to support water supply planning that accounts for uncertainty, learning, and flexibility using our best physical understanding of the system. This integration is enabled by the use of a statistical surrogate model, in this case an ANN trained on a MODFLOW model, which captures the dynamics of a non-linear physical model in a way that is computationally tractable. It allows us to use numerical methods for Bayesian uncertainty analysis for each possible head observation in each time period, corresponding to the full state space of the SDP.

This new method is applied using a simple groundwater model and planning formulation that allow us to demonstrate the approach with clarity. This formulation has limitations we must keep in mind in interpreting the results. The groundwater model is a lumped parameter, uncalibrated 2D model; the initial uncertainty in K and S is estimated using a recent hydrogeological study of the region. This approach does not capture the substantial spatial heterogeneity known to exist or detailed geologic information, and it should be interpreted as an approximation appropriate for assessing the first-order dynamic of long-term head decline. However, lumped parameter or zonal models can often have greater predictive power than more detailed alternatives which require more assumptions than can be justified with the available information [146, 44]. In our application, K and S can be interpreted as capturing information uncertainty in a parsimonious model rather than characterizing spatial heterogeneity. We use a single grid cell from the Buwayb well field at the center of Riyadh as a proxy for hydraulic head. This approach, while again an appropriate approximation for long-term head decline, does not capture the shape of the cone of depression in hydraulic head around Riyadh. Both the simple groundwater model and using a single proxy well impact the learning process shown in our results. A calibrated model may have had smaller initial uncertainty and therefore less learning at the outset. The presence of spatial heterogeneity may make learning more difficult. However, the presence of multiple wells may increase opportunities for learning.

The planning formulation assumes that groundwater pumping is either on or off and that the traditional, static planning alternatives are restricted to either building a desalination plant upfront or not at all over 30 years. In reality, restrictions on pumping could reduce rather than cutoff pumping. Similarly, if head decline made pumping infeasible in year 10, for example, planners would no doubt react before the end of the planning period in year 30. The specific quantitative comparison of expected value of the flexible approach to that of the static approaches should therefore be interpreted with caution. The goal is not to attempt to quantify the specific performance of the different approaches, but more broadly to assess whether there is value to invest in a flexible approach. The essential element of the flexible approach compared to a traditional approach is that a desalination plant can come online quickly in only two years, compared to a more typical 5+ year horizon. Therefore, while it is unlikely that many years of shortages would be tolerated, several years of shortages are still possible. The low sensitivity of the results to the shortage cost suggests that the value of flexibility would be similarly robust to changes in the duration of shortage.

Future work could extend this approach to more complex groundwater models and planning formulations and address a wide variety of groundwater systems and planning questions. Spatial heterogeneity in aquifer parameters could be addressed through a zonal approach to parameter estimation and the use of multiple monitoring wells. The ANN framework could accommodate this through a greater number of input and output parameters corresponding to different zones and multiple wells respectively; estimating the posterior over a greater number of dimensions could take advantage of MCMC methods if necessary. Initial analysis suggests that 5 wells, for example, could be accommodated into the SDP state space while still maintaining computational tractability; approximate SDP methods could be used for larger scale problems [127]. More active approaches to data collection could be tested; for example, as an alternative to passively collecting new head observations over time, the SDP formulation could include a decision variable to install new monitoring wells to collect information immediately.

In the planning formulation, a wider range of infrastructure or management alternatives such as adaptive pumping rates or demand reduction policies could be explored. Demand reduction measures have the potential to further reduce the need for expensive infrastructure investments; however, they have the potential to introduce further uncertainty given the difficulty in predicting human responses to incentives and restrictions. Wastewater reuse could also be explored as an infrastructure alternative, which would require extension of the framework to include constraints on water quality for different end uses. Evaluating these more varied alternatives would benefit from consideration of additional planning objectives. For example, desalination is a highly energy-intensive supply source; considering the energy and greenhouse gas intensity of different alternatives may further disincentive large desalination projects. Integrating the approach developed here for learning and flexible planning with the multi-objective simulation-based optimization approaches common in water resource systems analysis could address these limitations by enabling multi-objective evaluation of many alternatives in large-scale systems.

The value of information and flexibility are likely to vary substantially depending on the degree of uncertainty, planning decision, and water system. The high value of flexibility robust to deviations in the value of reliability may not hold in other applications with greater interactions with surface water and therefore stochastic variability or if infrastructure costs were less substantial or could achieve higher economies of scale. Exploring these elements in varied future applications can build theory around the drivers of and limits to flexible design and adaptive planning as an efficient and reliable approach for water supply planning under uncertainty. Our initial application of this method highlights the potential for Bayesian learning in combination with flexible planning to mitigate both cost and reliability risk in a poorly characterized groundwater system with unsustainable withdrawals. The prevalence of uncertainty and over-pumping in many groundwater supply systems highlights the potential for this approach to have widespread applicability.

Chapter 5

Bayesian updating of climate change uncertainty to enable flexible water infrastructure planning

This chapter has been adapted from a working paper: Sarah Fletcher, Megan Lickley, and Kenneth Strzepek, "Bayesian updating of climate change uncertainty to enable flexible water infrastructure planning", 2018.

Abstract: The design and planning of new water supply infrastructure must account for climate change in order to ensure reliability targets can be met over the infrastructure's multi-decade lifetime. However, climate change projections face substantial uncertainty in many regions. Recent work has focused on scenario-based approaches to develop robust planning strategies that perform well across many possible future climates. Robust approaches, however, face high risk of overbuilding expensive infrastructure if the worst outcomes are not realized. In this paper, we assess the potential for potential future climate observations to reduce uncertainty and enable flexible infrastructure approaches to mitigate overbuild risk without impacting reliability. To do this, we develop an integrated modeling approach that uses Bayesian model averaging to estimate and update dynamic model uncertainty estimates in climate change projections. These uncertainty estimates are used to characterize non-stationary climate change uncertainty in a stochastic dynamic program (SDP) to assess the potential to learn about climate change over time. We use engineering options analysis (EOA) to evaluate the value of flexible infrastructure design. We apply this framework to a

dam design problem in Mombasa, Kenya. We find high potential to reduce uncertainty over time and high value in a flexible dam design in which the dam can be raised in the future to increase storage capacity. The value of flexibility, however, depends on discounting and technology choice.

5.1 Introduction

Long-term planning of water supply infrastructure faces uncertainty in how the climate system will change and how those changes will impact local water resource systems. Climate change uncertainty can increase the vulnerability of a water supply system if its sensitivity to climate is strong and its adaptive capacity to respond is limited [3]. Recent work has addressed both the limitations in projections of climate change by GCMs [78] and developed approaches to planning under climate change that account for those limitations by developing planning strategies that render the water system relatively insensitive to climate change projections [149]. Identified sources of uncertainty in climate projections include: emissions scenario uncertainty; internal variability in the climate system; and structural differences across models due to differences in representations of physical processes, initial conditions, and boundary conditions [69]. The magnitude of these uncertainties — in particular, the influence of global geopolitics on greenhouse gas emissions — has led many researchers in the planning community to address climate change as a "deep uncertainty" which is so severe that probabilities cannot or should not be placed on the possible outcomes [165]. Much of this work uses non-probabilistic, scenario-based approaches to reduce the vulnerability of water infrastructure investments to climate change uncertainty by developing strategies that meet reliability goals and other performance targets in many possible future climates [92, 19, 87, 61, 89]. Early approaches such as Robust Decision Making (RDM) [93, 92] focus on static robustness, or preventing system failure under the largest number of possible future scenarios [165, 73]. These approaches are effective in developing strategies that meet performance goals in a wide range of future climates over several decades but can lead to expensive overbuild of capacity if the worst outcomes are not realized. The impacts of overbuilding are especially severe in resource-scarce regions of the developing world.

Many studies have highlighted the importance of adaptive management approaches to climate change in which managers adapt and react as uncertainties unfold over time [108, 121]. Adaptive management can enable reliability at reduced cost by developing plans to ensure short-term water needs are met without investing in permanent solutions before the long-term future is well understood. Recent methods such as adaptation tipping points [62] and dynamic adaptive policy pathways (DAPP) [61, 89] enable policymakers to identify tipping points or thresholds beyond which new polices will be needed. Identifying these thresholds — and the policies to be implemented if they are reached — in advance enables a planned adaptation approach in which adaptive policies are fully developed and can be nimbly executed when needed, reducing short-term transition risks [102]. Defining "dynamic robustness" as flexibility enabling a plan to change in response to changing conditions over time, Walker et al. (2013) raises the limitations of RDM to develop dynamic robust solutions and highlights the value of DAPP in achieving dynamic robustness [165].

However, adaptive approaches are more difficult in infrastructure planning, as infrastructure requires large capital investments (often on the order of hundreds of millions or billions of dollars) that can last for a century and are difficult to change [35]. In infrastructure planning, therefore, adaptive approaches can pose trade offs or risks to static robustness if short-term supply gaps due to droughts, for example, cannot be addressed quickly enough with adaptive infrastructure planning [12]. Some recent studies have started to integrate adaptive management into infrastructure planning approaches, explicitly accounting for the potential for short-term adaptive strategies such as water transfers and demand reductions to reduce or eliminate the need to build infrastructure [177]. Similarly, Beh et al. (2015) [12] built on prior approaches in sequencing water infrastructure investments [134, 84, 75] and static robustness approaches by including both flexibility and robustness as objectives in an iterative planning approach.

These approaches, however, have some important limitations in how they address flexibility in infrastructure. First, the types of flexibility addressed in these approaches is limited, focusing primarily on flexibility in management or operations of water systems rather than on flexibility in infrastructure itself. Flexibility can be incorporated into infrastructure in a variety of ways. Flexible planning processes can enable flexible timing, location, or type of infrastructure. For example, a staged development approach to infrastructure development in which capacity is developed modularly in smaller steps can reduce the risk of overbuilding capacity. Infrastructure can also be physically designed to be more easily retrofitted in the future [168]. In water infrastructure, this has been assessed in hydropower projects

[153] and desalination plant design [51]. Second, flexibility is a strategy or life-cycle system property for achieving other performance targets rather than a performance goal unto itself. Including flexibility as an optimization objective without assessing the value of flexibility in achieving performance goals fails to address this distinction. Proactive approaches to flexible infrastructure design and planning, in which preparations or investments are made upfront in order to enable future flexibility, have a cost. The benefit of the flexibility in achieving performance targets must be evaluated in order to asses whether this cost is justified.

An additional limitation of these approaches to flexibility is that while they account for changes in the *state of the system* to drive adaptive planning or operations, they do not account for changes in *understanding of uncertainty* to drive adaptation. The ROF metrics developed by [123] update the probability that a performance target will be violated based on the state of reservoir storage; historical data is used to assess how often a certain reservoir storage level has previously led to failures. This does not account for the ROF associated with a certain storage level to change over time as more information about the system is collected or the system evolves. This limitation is especially important in addressing climate change, where non-stationary runoff can substantially change the ROF associated with a certain system state over time.

We address these limitations through the development of a planning framework that integrates several existing analysis tools. Engineering options analysis (EOA), related to real options analysis in finance, identifies flexible infrastructure options that can be exercised in the future; Monte Carlo simulation methods are used to assess the performance of flexible approaches with options and compare them to static approaches without options [33]. Engineering options analysis can address two of the above limitations by 1) including "real-in-options" alternatives that include physical infrastructure design in addition to alternatives using levers in policy, planning, or management and 2) providing a framework to estimate the value of flexibility and its tradeoffs relative to traditional robust or static approaches. Additionally, the use of multi-stage stochastic dynamic programming (SDP) with non-stationary transition probabilities can enable the development of policies for exercising options that change over time as both the state of the system and the characterization of uncertainty are updated. While the computational expense of SDP has often limited its use with realistic simulation models, recent methods in water and other domains have enabled this integration through approximate methods [75, 127] and surrogate statistical models (e.g. Chapter 4 of this dissertation).

SDP requires the use of probabilistic approaches to characterizing uncertainty. This stands in contrast to the many approaches above which use non-probabilistic, scenario methods for addressing climate change uncertainty. However, climate change uncertainty has multiple sources. While emissions uncertainty is highly influenced by geopolitics and institutional decision-making, model uncertainty and internal variability are not subject to these forces. Different uncertainties of different types can be addressed uniquely in the same planning problem [51]. Previous work has shown that model uncertainty dominates long-term uncertainty in global mean precipitation change [70], and recent work has enabled probabilistic estimates of model uncertainty [156].

Probabilistic estimates for model uncertainty in climate change are typically developed by comparing and weighting individual model projections from ensembles of GCMs from the coupled model intercomparison project, phase 5 (CMIP5). CMIP5 has collected and validated a large number of GCM simulations from various modeling groups, where simulations are all forced by the same emissions scenarios, or representative concentration pathway (RCP), to allow for a consistent comparison across models. Several methods have been put forward to assess the uncertainty across models using ensembles of projections from CMIP [156]. An early approach by Räisänen and Palmer (2001) [130] derives probability distributions by assuming a "democratic" weighting in which each model projection is assumed equally likely. This democratic weighting of models is also adopted by the Intergovernmental Panel on Climate Change (IPCC), where the multi-model mean and standard deviation are used to characterize the trend and uncertainty in climate projections [78]. More recent research has used BMA, a statistical approach which weights models based on their ability to reproduce historical observations. For example, Giorgi and Mearns (2002) [55] present the "reliability ensemble averaging" methodology, which uses BMA-derived weights to estimate the mean and standard deviation of future change, assuming a normal distribution. Tebaldi et al. (2005)[157] and Smith et al. (2009) [148], extend this to develop a fully Bayesian approach that uses BMA-derived weights and MCMC methods to estimate a posterior without assuming normality.

This study develops an integrated modeling framework that addresses the impacts of model uncertainty in climate change projections on water supply planning. It uses and extends the Bayesian statistical model developed by Smith et al. (2009) [148] to develop probabilistic projections of change in 20-year mean temperature (T) and precipitation (P). These probabilistic estimates characterize uncertainty dynamically: they are updated in a Bayesian manner to account for potential future climate observations. The probabilistic projections are used to characterize the non-stationary transition probabilities in an SDP in which mean T and P comprise the states of the system. The change in T and P over a 20-year time period (ΔT and $\Delta\%P$ respectively) are treated as hypothetical future observations used in the Bayesian updating: this allows us to assess how uncertainty in change in ΔT and $\Delta\%P$ would shift as more information about climate sensitivity is collected over time. For example, high rates of temperature change in the first 20 years are more likely to beget rapid temperature change in the next 20 years. By including all the possible future climate observations and their impact on uncertainty in the transition probabilities of a stochastic dynamic program, we explicitly account for dynamic, non-stationary climate change in our planning. Finally, we use the SDP to develop policies for exercising flexible options for infrastructure design and planning, and then assess these policies using engineering options analysis. The overall approach for assessing flexible planning by taking a dynamic approach to uncertainty that accounts learning in response to future observations is described in more detail in Chapter 2 and illustrated in Figure 2-3. We demonstrate this integrated modeling framework on a dam design application in Mombasa, Kenya.

The remainder of this chapter is organized as follows. In section 5.2, we present the generalized framework for integrating dynamic, probabilistic assessments of model uncertainty in climate projections into a SDP to evaluate flexible infrastructure. Then we describe the application to a dam design problem in Mombasa, Kenya in section 5.3. Section 5.4 present results, and we close with conclusion and discussion in section 5.5.

5.2 Modeling approach

Assessing the impact of climate change uncertainty on water supply infrastructure planning requires integration of several components. Long-term estimates of climate change must be translated into the monthly runoff time series needed for dam sizing. In order to quantify model uncertainty in climate change and propagate its impacts through an infrastructure planning model, we develop an integrated modeling approach that combines Bayesian modeling of uncertainty, stochastic weather generation, a rainfall-runoff model, and a reservoir

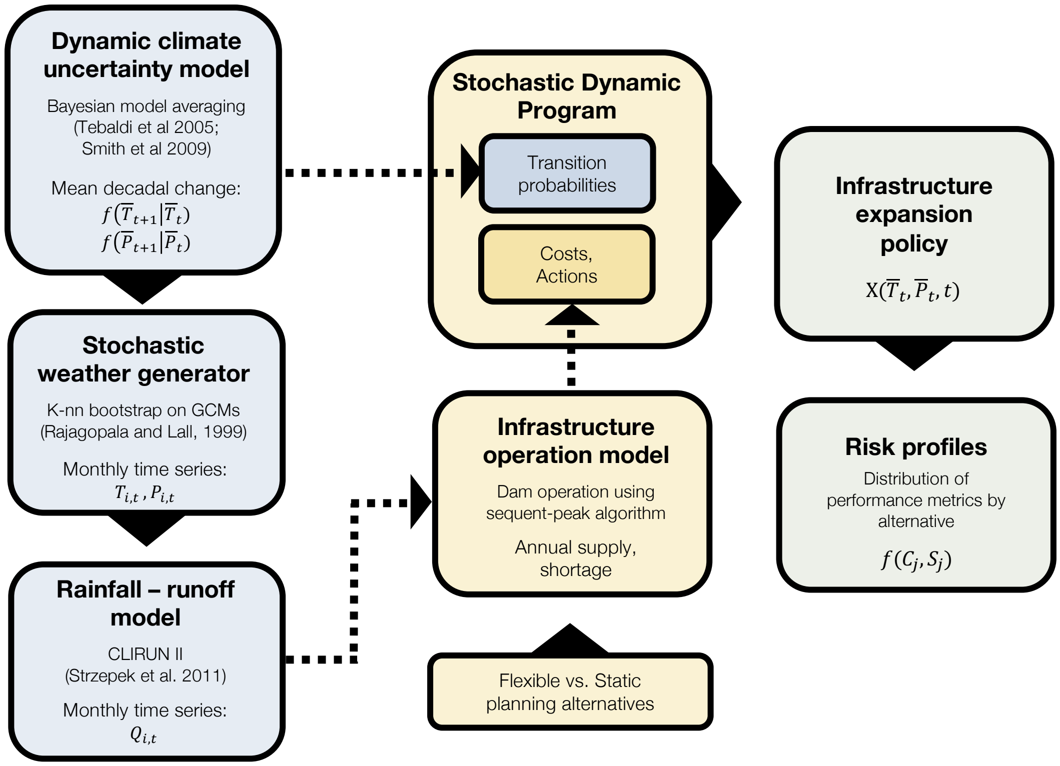

Figure 5-1: Schematic of integrating modeling framework to assess model uncertainty in climate change projections on infrastructure planning and assess the potential for Bayesian updating of uncertainty and flexibility to mitigate risk. Climate and hydrological modeling components are at left in blue; infrastructure planning and operations shown in center in yellow; integrated results at right in green.

operation model. These components are embedded in a SDP to develop and evaluate flexible infrastructure planning strategies against key performance metrics. A schematic of this process is shown in Figure 5-1, and each of the components are described below.

Stochastic dynamic programming (SDP)

SDP is an optimization approach that models decision-making under uncertainty over multiple stages or time periods. An SDP model is formulated by defining: a set of actions the decision maker can take, a set of states of the system, the cost of the actions as a function of the state of the system and the time period, and the transition probabilities. The transition probabilities characterize the uncertainty in the system by defining a probability distribution for state of the system in the next time period given the state and action in the current time period. These components are integrated into the Bellman equation, shown in equation 5.1, which is solved to develop an optimal policy, or the optimal action for each state in each time period.

$$V(s,t) = \underset{a \in A}{\operatorname{argmin}} \; C(s(t), a(t), t) \; + \; \gamma \sum_{s \in S} p(s(t+1) \,|\, s(t), a(t)) \, * \, V(t+1, s(t+1)) \quad (5.1)$$

where V is the optimal policy, t is the stage or time period, a is an action from a set of possible actions A, s is a state from the state space S, γ is the discount rate, and $p(s(t+1) \,|\, s(t), a(t))$ are the transition probabilities. In our application, the state space S comprises two climate variables important for runoff modeling, mean T and mean P over a 20-year period, as well as the type and amount of infrastructure capacity added. The action space A describes the amount of infrastructure capacity for a dam or desalination plant at the outset of the planning period, and then whether infrastructure capacity is expanded in later time periods. Future applications could also include other water planning and management alternatives such as other infrastructure alternatives, reservoir operations, and demand-side policies. The costs C include the capital and operating costs of infrastructure capacity additions as well as damages if the infrastructure fails to meet reliability targets. Bayesian modeling of climate change uncertainty is integrated into the optimization framework through the transition probabilities. Transition probabilities $p(T_{t+1}|T_t)$ and $p(P_{t+1}|P_t)$ are developed using the Bayesian modeling approach described in the next section.

We develop a novel approach in which each of the T and P states in the SDP state space are treated as hypothetical, future observations and used to develop updated posterior distributions that account for that observation. For example, let us assume that 40 years from now, we observe a mean T of 28 degrees Celsius (°C) and mean P of 68 mm/month. This suggests a rapid warming and drying trend. We use those values as observations in our Bayesian analysis to develop an updated posterior for change in T and P over the next 20 years, and that posterior is used to characterize $p(T_{t=3}|T_{t=2} = 28)$ and $p(P_{t=3}|P_{t=2} = 68)$ where t is measured in time steps of 20 years. These particular posteriors would have higher probability on warm and dry states in the next time period than the prior. This analysis is repeated for every possible climate observation in each time period to develop transition probabilities that reflect Bayesian learning based on each potential future climate.

This approach enables us to address two limitations in many current approaches to water supply planning under climate uncertainty: 1) the ability to characterize uncertainty dynamically so that it can be updated over time, and 2) the development of flexible strategies that depend on the state of the system and time period. Non-stationary transition probabilities in which the probability distribution of change in T and P can vary with time are used to characterize expected non-stationary change in the climate system. Similarly, deriving an optimal policy which identifies unique optimal actions for each state and time period can be used to develop flexible strategies for if, when, and how to add or change infrastructure as we observe climate change over time. The optimal policy, therefore, includes decision rules for whether to add infrastructure given a certain observed T and P in each time period; this defines thresholds for T and P beyond which additional capacity should be added.

Bayesian modeling of climate change uncertainty

To characterize the transition probabilities described above, we extend the Bayesian statistical model presented in Smith et al. (2009) [148]. The statistical model of Smith et al. (2009) treats historical temperature observations X_0 as realizations of a random variable X whose unknown mean μ reflects the underlying mean temperature of the current climate. Similarly, future temperature projections are treated as realizations of a different random variable X' whose unknown mean μ reflects the underlying mean temperature of the future climate. Weights or reliabilities of each individual GCM projection j from a set of M models are estimated using the difference between the historical projection X_j and the historical observations; larger differences indicate that X_j must have a higher variance and therefore model j a lower reliability [148].

We extend this approach in three ways. First, we apply the model to P as well as T. We assume that T and P are independent, reflecting that a model's performance in estimating T may be unrelated to its ability to estimate P. Second, we apply the model to observations and projections of change in T and P rather than absolute T and P due to greater model skill in GCM projected changes in temperature and precipitation rather than absolute values [107, 131]. This is especially important in our application in Mombasa where there is less disagreement in temperature change than there is disagreement in hindcasted absolute temperature. Finally, we apply the model to multiple time periods in series. Smith et al. (2009) assumed two periods: a historical climate (1961-1990) and a future climate (2071-2100). We use pairs of 20-year time periods from 1980 to 2100, in which the "historical" climate corresponds to the time period in the SDP and the "future" climate corresponds to the next 20-year period; this provides the 1-stage transition probabilities needed in the SDP.

Following [148], the statistical model is formulated as follows for ΔT; an identical model is used for $\Delta\%P$.

$$
\begin{aligned}
X_0 &\sim N(\mu, \lambda_0^{-1}) \\
X_{j,t} &\sim N(\mu, \lambda_j^{-1}) \\
X_{j,t+1}|X_{j,t} &\sim N(\nu + \beta(X_j - \mu), (\theta\lambda_j)^{-1})
\end{aligned}
\tag{5.2}
$$

where μ, ν, β, θ, and λ_j have prior distributions:

$$
\begin{aligned}
\nu, \mu, \beta &\sim V(-\infty, \infty) \\
\theta &\sim G(a, b) \\
\lambda_1 ... \lambda_j &\sim G(a_\lambda, b_\lambda) \\
a_\lambda, b_\lambda &\sim G(a^*, b^*)
\end{aligned}
$$

The joint density of μ, ν, X_0, $X_{j,t}$, $X_{j,t+1}$, β, θ, a_λ, b_λ, and $\lambda_j \, \forall j = 1...M$ is therefore proportional to:

$$
\theta^{a+M/2-1} e^{-b\theta} e^{(1/2)\lambda_0(X_0-\mu)^2} a_\lambda^{a^*-1} e^{-b^* a_\lambda} b_\lambda^{a^*-1} e^{-b^* b_\lambda}
$$
$$
\times \prod_{j=1}^{M} \left[\frac{b_\lambda^{a_\lambda} \lambda_j^{a_\lambda} e^{-b_\lambda \lambda_j}}{\Gamma(a_\lambda)} e^{-(1/2)\lambda_j (X_{j,t}-\mu)^2 - (1/2)\theta\lambda_j \{X_{j,t+1} - \nu - \beta(X_{j,t}-\mu)\}} \right]
$$

X_0 is the observed ΔT in time period t; $X_{j,t}$ is model j's projection of ΔT in the current time period t, and $X_{j,t+1}$ is model j's projection of ΔT in the next time period $t+1$. X_0, $X_{j,t}$, and $X_{j,t+1}$ are treated as observations from unique normal distributions. μ and ν are the underlying means for the 20-year ΔT distributions in the current (t) and future ($t+1$) time periods respectively. The goal of the analysis is to estimate a posterior distribution for ν, which will characterize the transition probabilities. We set $a = b = a^* = b^*$ which were chosen so that θ, a_λ, and b_λ have proper but diffuse priors. In the above distributions, N, U, and G represent normal, uniform, and gamma distributions, respectively. λ_j is the inverse variance of X_j, representing the reliability of model j. β is a regression parameter that introduces correlation between $X_{j,t}$ and $X_{j,t+1}$; it is estimated by the model rather than assumed. θ is also an estimated parameter that enables a model to have different reliability in the future compared to the present. The marginal densities for each of the parameters are estimated using MCMC methods; we use the Gibbs sampling approach and code developed in [148]. More details on the statistical model are available in Smith et al. (2009) [148].

In order to characterize the transition probabilities, the statistical analysis is replicated for each climate state in each time period. The temperature state in the SDP is treated as the observed temperature X_0 in equation 5.2. The resulting posterior marginal distribution for ν is discretized, translated from ΔT and $\Delta\%P$ to absolute values of T and P, and used as the transition probability for that temperature state. This process allows us to simulate learning over time as more climate observations are collected; the transition probabilities in the later time periods incorporate more information about how the climate has changed.

Stochastic weather generation

Climate impacts on river runoff depend on changes in month-to-month variability in precipitation and temperature in addition to changes in the mean. We model these two changes separately. To develop monthly time-series of T and P, we follow the k nearest neighbors (kNN) approach as described in Rajagopalan et al., (1999) applied to GCM projections. This non-parametric statistical approach allows us to impose the mean T and P from the SDP while also capturing the standard deviation in monthly values and month-to-month autocorrelation projected by the GCMs. This approach was chosen for its simplicity and ease of implementation; future studies could use other non-parametric approaches such as the local polynomial regression method developed in [17].

Rainfall-runoff model

Next, the synthetic T and P time series are input to a hydrological model to asses the impacts on runoff. We use CLIRUN II, the latest in a family of hydrological models developed to assess the impact of climate change on runoff [152, 151, 174, 83]. CLIRUN II is a two-layer, conceptual, lumped-watershed rainfall-runoff model. It averages soil parameters over the watershed and models runoff at one gauge station at the mouth of the basin. It can be run on a monthly or daily time step. Using the 100 T and P monthly time series as inputs, CLIRUN II generates 100 monthly time series for runoff.

Infrastructure alternatives and operations

A key outcome of this approach is to assess the value of flexible water supply infrastructure planning in mitigating climate uncertainty. To do this, our approach develops flexible infrastructure alternatives and compares them to static approaches. Two static alternatives are developed: one designed with enough capacity to meet reliability targets under today's climate, and another "robust" alternative designed to meet reliability targets under any of the possible future climates projected by the Bayesian climate uncertainty analysis. Then a flexible alternative is developed in which the smaller amount of capacity sufficient under the current climate is installed initially, but plans are made to be able to expand to the full robust capacity in the future if needed. The performance of these alternatives is evaluated using infrastructure operation models, which estimate the yields obtained from each of the alternatives for each of the generated time series for runoff in the watershed. Yields are compared to demand and reliability targets to estimate unmet demand or water shortages under each possible future climate state. These shortages, in combination with cost estimates for the capital and operating costs of the different infrastructure alternatives, are used to characterize the cost function in the SDP.

Simulated risk profiles

Finally, the SDP results develop a policy for whether to invest in the flexible or static alternative and, if the flexible alternative is chosen, under what climate states it should be expanded. We develop forward simulations for different climate change paths by sampling from the transition probabilities. We use these simulated climate change paths to assess the performance of the different alternatives when they operate according to the policies developed by the SDP. We develop distributions for the performance against key performance metrics including cost and reliability.

5.3 Application to Mwache dam

Background

We demonstrate this method with an application in Mombasa, a coastal city in Kenya. Mombasa is the second largest city in Kenya with an estimated population of 1.1 million

[24]. Urban water demand is currently estimated at 150,000 m^3/d and expected to grow to 300,000 m^3/d by 2035 [119]. Mombasa has a warm, humid climate with average annual precipitation of about 900 mm/y and a mean annual temperature of about 26°C [118]. Precipitation is driven by monsoon winds with two rainy seasons: a long rainy season from April to June with average monthly precipitation of 113 mm/month and a shorter rainy season from October to November with average monthly precipitation of 90 mm/month. The World Bank is financing a dam project on the nearby Mwache River to address water scarcity in the region and expected demand growth [170, 114]. The dam is targeted to supply a firm yield of 186,000 m^3/d (67.9 MCM/y) at 90% reliability for urban demand with excess for agricultural supply. The Mwache catchment covers approximately 2250 km^2 west of Mombasa[25]. Mombasa, the Mwache river, and the proposed dam location are shown in figure 5-2. Mean annual runoff (MAR) is 113 MCM per year [25].

Uncertain projections of climate change in the region make it difficult to assess how large to size the dam in order to meet the yield and reliability targets over its full lifetime. While there is robust agreement across GCMs projecting warming in the region, precipitation response is more uncertain. While Held and Soden (2006) established the well known 'wet-get-wetter, dry-get-drier' hydrological response to global warming, this mechanism was shown to break down over land in the tropics [72]. Uncertainties in the rainfall response in the tropics are driven by thermodynamic changes and large scale dynamical changes such as shifts in convergence zones in response to changes in sea surface temperature [26]. Therefore, there is also substantial uncertainty in whether runoff and yield, which are primarily driven by precipitation in this region, will increase or decrease as well. A previous study commissioned by the World Bank has assessed the climate vulnerability of the Mwache dam [171]. This study uses an ensemble of 121 climate projections from CMIP3 and CMIP5 and applies RDM to evaluate design storage options ranging from 40 MCM to 140 MCM; they recommend designs ranging between 80 and 120 MCM. [171].

Infrastructure alternatives and demand scenarios

We apply the framework developed in section 5.2 to develop a flexible dam design in which extra storage capacity can be added in the future and assess its performance in comparison to static alternatives. We hypothesize that by explicitly addressing the opportunity to learn about climate change over time and update uncertainty estimates, a flexible design will

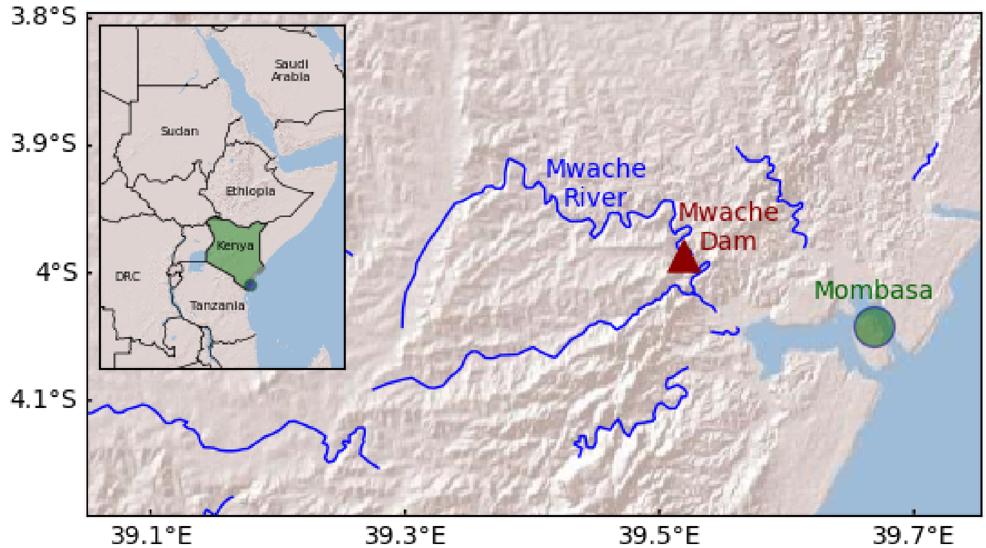

Figure 5-2: Map of study area including Mwache river, proposed dam location, Mombasa city center.

perform favorably. We apply this framework to two planning scenarios. In the low-demand scenario, we assume a target yield of 150,000 m^3/d (54.8 MCM/y) with 90% reliability from the Mwache dam; this yield target reflects current demand and can be fully met by the new dam. We evaluate the two dam sizes proposed by the previous World Bank study [171], 80 MCM and 120 MCM, as well as a flexible alternative in which the height of the small dam can be raised, increasing the reservoir capacity to 120 MCM. Our analysis using CLIRUN II and the reservoir sizing model confirms that the 80 MCM dam meets the reliability targets in the current and expected future climate but does not meet reliability targets if the climate gets substantially warmer and drier. The 120 MCM dam meets reliability targets across all projected future climates, providing a robust alternative. Cost estimates for the small and robust dams were developed using the cost tool from the previous World Banks study [171]. For the flexible dam, the cost per m^3 of additional capacity added is assumed to be 50% greater than that of the original capacity.

In a second, high-demand scenario we assume a target yield of 300,000 m^3/d (109.6 MCM/y) with 90% reliability, reflecting the potential for rapid demand growth in the next decade. This high value of demand is consistent with 2035 projections from [119]. In this scenario, the target yield is greater than the mean annual runoff in the Mwache river and therefore the dam cannot meet the target yield regardless of its size. We model the combination of a 120 MCM dam and a desalination plant that is used to supply demand when reservoir storage is low. Three desalination alternatives are chosen, analogous to the dam design alternatives. A low capacity alternative designed to meet reliability targets in the current and expected future climate has 60 MCM of capacity; the robust alternative that meets the reliability targets across all projected future climates has 80 MCM of capacity; a flexible alternative starts with 60 MCM and can be expanded to 80 MCM. Capex and opex estimates for the desalination plans were developed using the Cost Estimator tool from DesalData [56]. Evaluating this second scenario allows us to compare the value of flexibility across two technology options, earthen dams and desalination, which have unique water supply profiles and cost structures. These planning scenarios, and the cost and capacity of the infrastructure considered in each, is summarized in Table 5.1.

Table 5.1: Key planning scenarios and corresponding infrastructure evaluated

	Demand Scenario	Technology	DR	Capacity [MCM]		Capex [M$]			
				Small	Large	Small	Large	Exp	Flex + Exp
a	Low	Earthen dam	3%	80	120	76.5	99.2	49.6	148.8
b	Low	Earthen dam	0%	80	120	76.5	99.2	49.6	148.8
c	High	RO desalination	0%	60	80	183.1	232.2	72.4	255.5

Climate and hydrological analysis

To implement the Bayesian uncertainty analysis in Mombasa, we use a total of 21 CMIP-5 members whose modeling group and model run are included in the appendix. For each GCM, monthly temperature and precipitation values are averaged over 2°S to 6°S and 38°E to 42°E, overlaying the Mwache catchment; GCM projections are regridded from their original resolution following the approach in Boehlert (2015) [18]. The same is done for the observed climate, where monthly values are taken from the Climate Research Unit (CRU) dataset version TS.3.21 [118]. The analysis is repeated for the five 20-year time periods starting with 2001-2020 for t=1 and ending with 2081-2100 corresponding to t=5 in the SDP. The 20-year time interval was chosen so that year-to-year variability was not driving the trend in precipitation and temperature across time periods.

The hydrological model CLIRUN II is calibrated using 14 years of monthly streamflow data. Only one streamflow gauge, RGS 3MA03, is available in the Mwache basin [25]. However, it is directly upstream of the dam location, making it representative for this study. The same monthly temperature and precipitation data from CRU used in the Bayesian climate analysis is used to calibrate CLIRUN II for consistency. This temperature and precipitation data is different than the local data used in the previous World Bank study [171], leading to different calibration results but similar performance (historical MAR: 113 MCM/y; World Bank MAR: 133 MCM/y; our MAR: 103 MCM/y). The infrastructure operation model includes dam operations (and desalination operations when necessary) that seek to meet the specified yield target while accounting for dead storage, net evaporation, and environmental flows. Unmet demand is measured for each of the 100 streamflow time series, and the average 20-year unmet demand is used to characterize U in the SDP formulation in equation 5.3. More details on the implementation of CLIRUN II and the operation model are in the appendix.

SDP formulation

These two planning scenarios are modeled using the SDP framework depicted in figure 5-1. The components of the SDP shown in equation 5.1 are formulated as follows:

$$\begin{aligned} S &= \{T(t), P(t), Z(t)\} \\ A &= e(Z,t) \\ C &= I(T,P,Z,e,t) + D * U(T,P,Z,e,t) \end{aligned} \tag{5.3}$$

where

- $t \in \{1...5\}$ is a 20-year time period ranging from 2001-2020 for $t = 1$ to 2081-2100 for $t = 5$
- $T(t)$ is the mean temperature in °C in time period t, ranging from 25 to 33 at 0.05°C increments.
- $P(t)$ is the mean precipitation in mm/month in time period t, ranging from 66 to 97 at 1 mm/month increments.
- $Z(t) \in \{1...4\}$ is the available infrastructure, in which the states correspond to a small infrastructure alternative, large infrastructure alternative, flexible unexpanded alternative, and flexible expanded alternative, respectively. The infrastructure alternatives are either a set of dams or a set of desalination plants.
- $e(Z,t) \in \{0...4\}$ is the choice of infrastructure in which 0 is no change, 1 is a small alternative, 2 is a large/robust alternative, 3 is a flexible alternative, and 4 is the expansion of the flexible alternative. The alternatives include a set of dams or a set of desalination plants. The choices are constrained by time period and available infrastructure such that $e(Z, t = 1) \in \{1, 2, 3\} \forall Z$; $e\{Z, t\} \in \{0, 4\} \forall t = 2...5, Z = 3$; and $e\{Z, t\} \in \{0\} \forall t = 2...5, Z = 1, 2, 4$
- I is the cost of the infrastructure including capital costs (capex) and operating costs (opex). Desalination opex is a function of the water produced in each time period.
- D is unit cost of damages incurred for unmet water demand, set at 15 \$ /m^3 in our base case based on estimates of water productivity in Kenya from the World Bank [158].

- U is the volume of unmet demand as a function of the climate states, existing infrastructure, and any new infrastructure brought online in time t. U=0 in t=1, reflecting that t=1 is a planning and construction period and performance is not measured until the beginning of the second 20-year time period.

5.4 Results

Here we present results from the application of the modeling framework to Mombasa. First, we show results from the Bayesian uncertainty analysis demonstrating the reduction in uncertainty compared to a democratic weighting and the potential to reduce uncertainty by incorporating new information over time. Then we present results from the SDP showing the flexible policy for the SDP and its performance in comparison to the two static alternatives. We first present these results for our base case (scenario a: low demand with discounting) and then discuss how the results change without discounting and with desalination in the high demand scenario.

Bayesian climate uncertainty analysis

Figure 5-3 shows historical T and P from CRU and projected change in T and P from each of the GCMs. Then, confidence interval (CI) using first the IPCC democratic weightings in which all models are assumed to perform equally well are compared to CIs generated from the Bayesian uncertainty analysis for the first time period. We see that the CIs from the Bayesian analysis have a smaller range of uncertainty in comparison both the full range of the individual projections as well as the democratic weighting. This is because the Bayesian analysis puts most of the weight on a subset of models that match historical change in this area better than the others.

The process of updating uncertainty over time using the Bayesian analysis from later time periods is shown in Figure 5-4. We present one sample time series of how the climate states T and P could evolve over time. For each simulated observation in the time series, we use the transition probabilities to simulate 10,000 time series starting at the current observation and going to the end of the planning period. These time series are used to construct a 99% CI. This process is repeated for each time period, with darker colors in the plot corresponding to the CIs developed with more observations later in the planning period. This approach

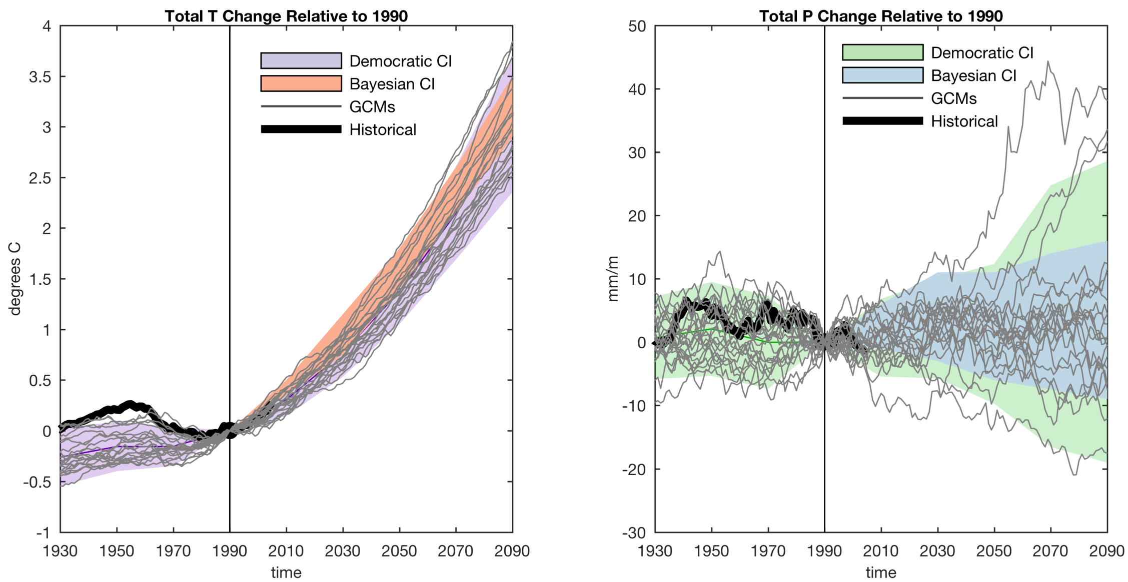

Figure 5-3: Modeled and observed temperature (left) and precipitation (right) relative to 1990 values with uncertainty estimates. The gray lines are 20-year moving averages of GCM simulations in the grid cells over Mombasa. The purple (left) and green (right) shaded regions show CIs using the democratic IPCC method for characterizing uncertainty plotted at 20-year increments. The orange (left) and blue (right) shaded regions show the 90% CI developed using the Bayesian uncertainty method applied in the first time period. The Bayesian CIs are narrower than the democratic CIs, demonstrating the ability to reduce uncertainty by taking advantage of the additional information that some models perform better in this region than others.

allows to compare how the uncertainty at the end of the planning period in 2100 changes as more observations about temperature and precipitation are collected over time. The top half of Figure 5-4 shows this process for temperature and precipitation, for which the simulated observations are sampled independently. In both cases, the CIs narrow over time, demonstrating the value of more information in reducing predictive uncertainty. Sometimes, however, a new observation does not reduce the uncertainty at the end of the planning period. This is seen with 2010 temperature estimate; the updated CI completely overlaps the previous. This suggests that value of information can be limited by the noise inherent in the statistical model, especially when the simulated observation is close to the center of the previous CI. Figure 5-4 shows a single sample time series of potential observations; a different time series, for example, may show a decreasing rather than increasing precipitation trend, in which case the precipitation CI would narrow closer to the bottom of the initial uncertainty range.

The bottom half of Figure 5-4 shows how the same simulated temperature and precipitation observations update uncertainty in MAR and water shortages. MAR correlates closely with precipitation, especially in the first half of the planning period. In the second half of the planning period, more rapid temperature increases offset modest increases in P, showing a slight decline in MAR. The learning profile is similar to that of P. Mean annual water shortages, at bottom right, are measured against a 90% monthly reliability goal: the first 10% of shortages in any month do not incur damages. This plot assumes the low-demand scenario (55 MCM/y) with the small dam (80 MCM of reservoir capacity). Here we see strongly asymmetric uncertainty; the lower bound of the CI is 0. This reflects the low-probability, high-severity risk of droughts; shortages occur only when runoff is substantially below MAR for several months or years in a row. In this sample time series, the modest increase in temperature and relative stability of MAR are enough to substantially reduce the 90th percentile risk over time. An alternate version of this figure is shown in Appendix C in which small decreases in P in combination with high warming drives MAR down and the risk of shortages substantially higher. Across many different simulated T and P observations we find a similar trend of narrowing of uncertainty, regardless of the direction of change, demonstrating a robust high value of information.

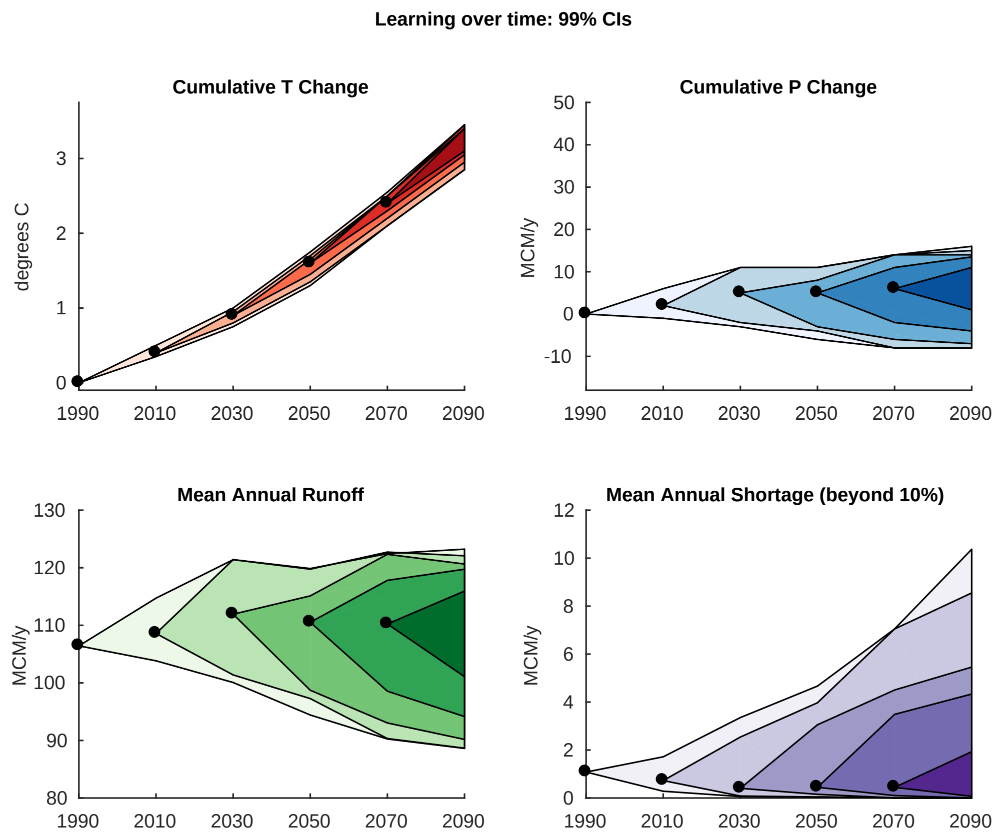

Figure 5-4: One sample realization of Bayesian learning over time. Black dots represent a single simulated time series for potential future climate observations. These simulated observations are used to develop and update probabilistic estimates for change represented using 99% confidence intervals for projected change in T, P, MAR, and water shortages. In this example, modest increases in P lead to stable MAR, allowing us to eliminate the risk of high shortage values by the end of the century. An alternate simulated time series with decreasing P and increasing shortage risk is shown in the appendix. Across many simulated time series we find robust high value of information, demonstrated by reduction in CI range.

SDP

The previous analysis demonstrated the ability of the Bayesian uncertainty analysis to reduce uncertainty over time through the use of simulated potential future observations of T and P. These simulated observations correspond to the states of the SDP. In this way the SDP accounts for all the possible future observations and their probabilities and chooses an optimal strategy based on all the possible learning outcomes. This optimal strategy results in two main outcomes, shown in Figure 5-5. In the first time period, shown in panel a) at left, the SDP develops a threshold as a function of T and P in the first 20-decade time period beyond which the large robust infrastructure is optimal; lower than this threshold the flexible alternative performs better. This is because the relatively small cost difference between the flexible and large dam means that if the risk of shortages at the outset is high enough, it is better to invest in the robust option upfront. In time periods 2 through 5, the SDP policy results in a T and P threshold beyond which the flexible infrastructure capacity is expanded if available; this is shown on the right side of the figure. Similar to the first period policy, expanding infrastructure capacity is optimal in drier and warmer states. The threshold moves somewhat left in the plots in the later time periods. This is because a modest shift towards warmer and drier climate in the early time period signals that further warming and drying is expected. The same modest shift in later time periods indicates a slower rate of warming and drying, suggesting that the risk of rapid transition to a state where water shortages are likely is lower.

Forward simulation

We now present results showing how the flexible strategy developed by the SDP performs against the static alternatives. The transition probabilities are used to simulate 1000 time series for the climate states, and the optimal policies are used to assess how the alternatives would perform in each time series. Figure 5-5 shows histograms for the decisions made under the optimal policies across the 1000 simulations; the top row corresponds to the low-demand scenario a) discussed here. At top left, we see that the flexible alternative is chosen in 90% of simulations under the low-demand dam scenario with a base case discount rate of 3%. At top right, we see that when the flexible alternative is chosen, the option to expand is never expanded in about 70% of simulations, highlighting the relatively low

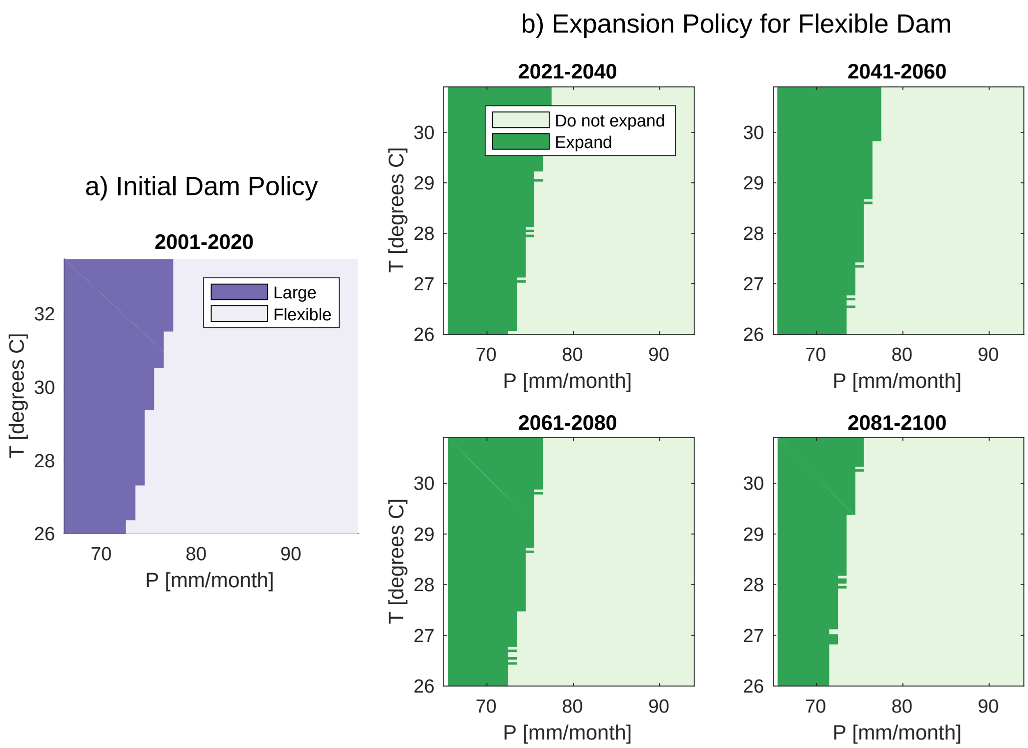

Figure 5-5: Optimal policies from SDP results. Panel a) at left shows the initial dam decision and the four panels b) at right show the policy for exercising the option to increase height of dam. Results are shown for the low demand dam scenario under 3% discount rate. The robust dam is chosen for hotter, drier climates in the first time period. Similarly, the flexible option is exercised if the climate transitions to a hot, dry climate in later time periods. The expansion threshold shifts in later decades. This is because a modestly hotter and drier climate in early time periods signals more rapid change in the coming decades through the learning process.

probability risk of transition to a climate that is substantial drier enough to lead to shortages beyond 10% of demand. The time period at which it is exercised varies; sometimes rapid warming and drying leads to an early expansion decision while sometimes the change is more gradual. There are relatively few expansions in the final time period. This reflects a known limitation of finite-horizon SDP formulations; they discourage investment toward the end of the planning period because there is limited time to reap the benefits of those investments. In reality, however, those investments would bring benefits after the end of the planning period.

Finally, we compare the performance of the flexible strategy following the optimal policy with the two static alternatives against the objective function C of the SDP in equation 5.3. Figure 5-7 shows CDFs of the total cost of each alternative across the 1000 forward simulations; the top row shows planning scenario a) discussed here. The large robust static alternative, shown in blue, has the same cost (equal to the capital cost of the dam) across all simulations; as designed, no shortage damages are incurred in any of the simulated future climates. The small dam, shown in orange, has the most variable costs. It performs better than the large dam in about 70% of simulations, but has substantially higher costs in 30% of simulations due to large damages from water shortages. The flexible alternative has the same cost as the small dam in close to 70% of simulations, but the reliability risk is substantially mitigated because of the potential to expand. The high-end costs are higher than the robust alternative because 1) the cost of building the 80 MCM dam and expanding to 120 MCM is higher than building the 120 MCM dam upfront and 2) sometimes the dam is not expanded even when modest water shortages are incurred. The ability of the flexible alternative to mitigate both the the risk of overbuilding and the risk of severe shortages demonstrates the high value of flexibility in this case.

Alternative scenarios

We now assess how the value of flexibility changes 1) without discounting and 2) under the high demand scenario. Results for these two scenarios are shown in panels b) and c) of Figures 5-6 and 5-7. We see in the low demand, no discounting scenario a) that the value of flexibility in our base case was largely driven by discounting, which incentivizes delays in capital investments. With a 3% discount rate, when the flexible dam is expanded 40 years in the future, the cost of flexible dam plus is expansion is 4% more expensive than building

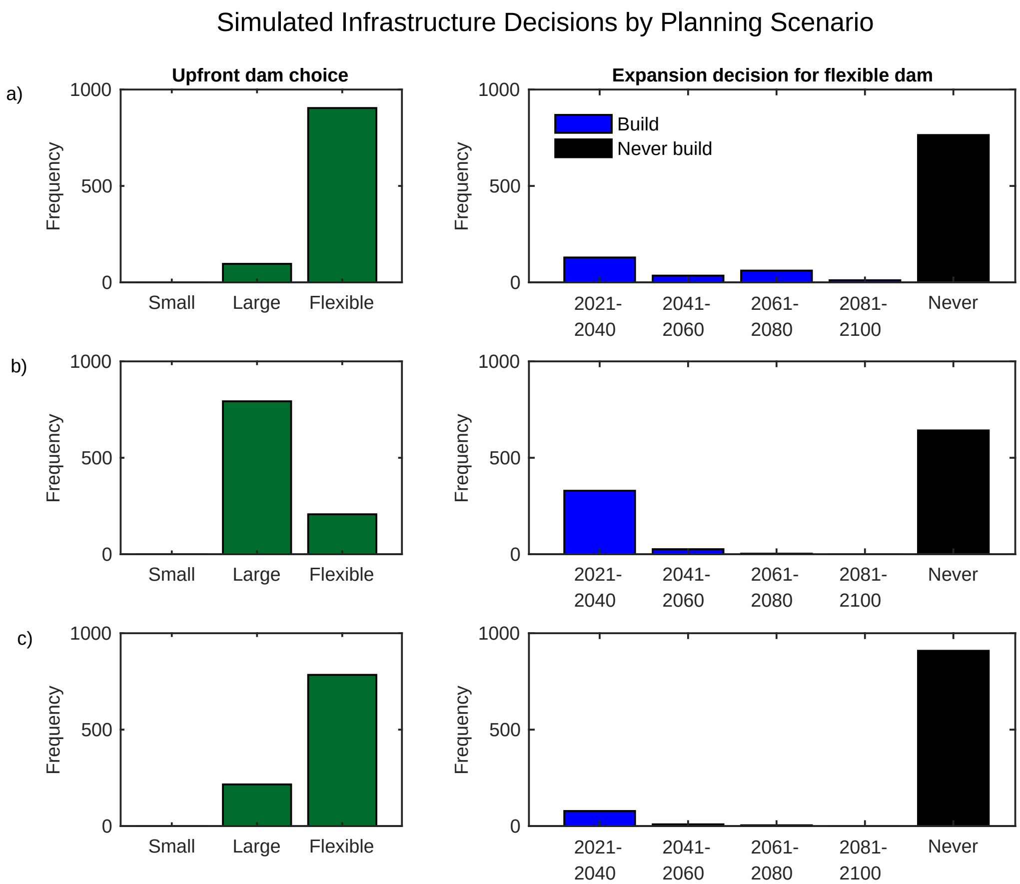

Figure 5-6: Histogram for infrastructure decisions. Top row: scenario a) low demand with discounting; middle row: scenario b) low demand without discounting; bottom row: scenario c) high demand without discounting. In each row, the left plot shows the initial decision of which alternative to choose in the first time period. The right plot shows, when the flexible dam is available, how often it is expanded and when it is expanded. The flexible alternative is chosen most often in scenario a) because discounting incentivizes delayed capital investments but not in b) because large economies of scale incentivize a single, large investment. In scenario c), more modest economies of scale lead to high value of flexibility in the absence of discounting. Across all scenarios, the flexible dam is expanded in no more than a third of simulations, highlighting the low probability of risk of reaching a climate that is hot and dry enough to incur substantial shortages.

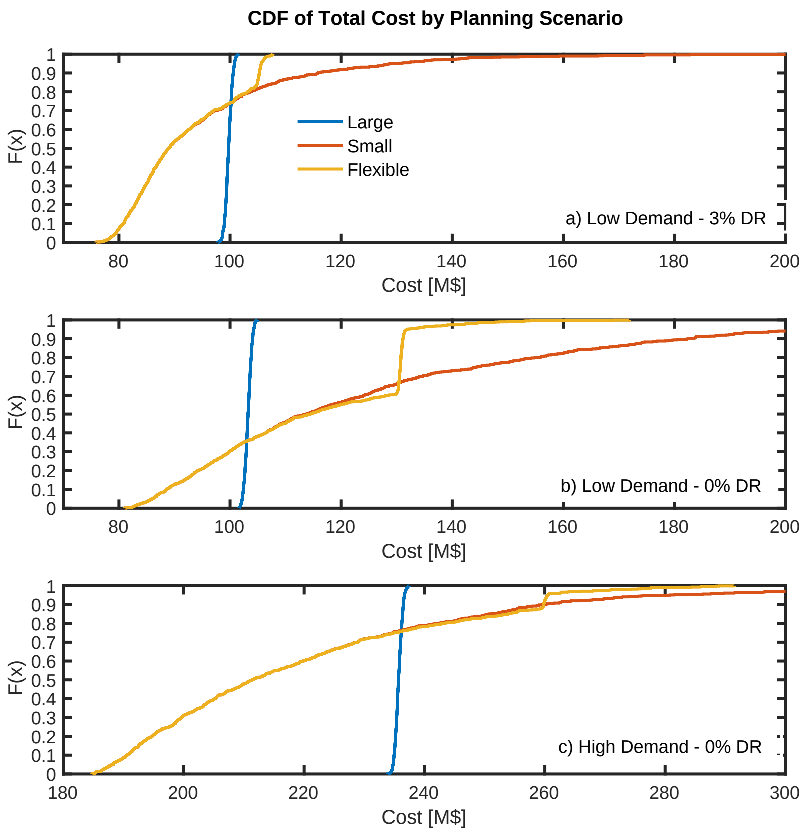

Figure 5-7: CDF of total cost for each infrastructure alternative by planning scenario. Top: scenario a) low demand with discounting; middle: scenario b) low demand without discounting; bottom: scenario c) high demand without discounting. Each plot compares the small and large static alternatives, shown in blue and red, compared to the flexible alternative shown in yellow. The ability of the flexible alternative to reduce risk of over building is demonstrated by its low cost in the low percentiles in all three scenarios. The flexible alternative also mitigates large reliability outages in comparison to the small static alternative, demonstrated in the high percentiles. However, the median cost of the flexible alternative is higher than the large robust alternative in scenario b) due to substantial economies of scale.

the large dam upfront, compared to 27% more expensive without discounting. Without discounting, the robust dam looks more favorable; it performs best in 60% of simulations, has no cost variability risk, and is chosen upfront in about 75% of simulations. The low value of flexibility without discounting is driven by the cost structure of the technology; large economies of scale in the dam mean that an 120 MCM is only 30% more expensive than an 80 MCM dam for 50% additional capacity. This suggests it is often better to build the large dam upfront even if there is a relatively low probability that it will be needed. The high-demand scenario in which a 120 MCM dam is combined with a desalination plant shows a high value of flexibility even without discounting. The flexible alternative is chosen upfront in over 80% of forward simulations, and the CDF demonstrates that it outperforms the static alternatives by substantially mitigating the over build risk in comparison to the robust alternative and also modestly reducing the shortage damage risk in comparison to the small alternative. While the flexible alternative only reduces cost at the 90th percentile and above, this substantially reduces the expected value as the maximum cost of the small plant reaches almost M$400 (truncated on plot). In this case, the economies of scale for a desalination plant are much less substantial. These results highlight differences in the value of flexibility across technologies.

5.5 Discussion

The results in the Mombasa application demonstrate both the value of information and flexibility in managing climate change uncertainty as well as its limitations. In the low-demand scenario we see a high value of flexibility when costs are discounted, but limited value of flexibility without discounting. In the high-demand scenario we have high value of flexibility regardless of discounting. We measure the value of flexibility by assessing not only the expected value of performance against the two objectives cost and reliability, but the value-at-risk and value-at-gain as measured by the 10th and 90th percentiles respectively. This highlights that although the uncertainty and learning is driven by the climate system, decisions about whether flexibility is a valuable tool in mitigating uncertainty are strongly influenced by technology choice and cost structure. Large economies of scale make flexibility less valuable; it is better to choose a robust alternative when it is not much more expensive to do so. However, delaying capital investments also provides financial value, which can be especially impactful in resource-scarce areas where unused capital could support other critical infrastructure services.

The value of flexibility is also driven by opportunities for learning about future risk of water shortages by incorporating new climate observations. The planning framework developed here accounts for learning in both the evolution of the state of the system over time and also for learning in how the risk of being in a certain system state changes over time. For example, being in a climate with mean T of 28°C and mean P of 70 mm/month poses a greater risk to future water shortages if that state has been reached rapidly over a short time period. The use of multi-stage stochastic planning can be used to explicitly model learning about uncertainty through the use of non-stationary transition probabilities characterized by the Bayesian climate uncertainty analysis. It also accounts for risk that depends on the state of the system by developing an infrastructure policy that varies with the current state of the system. By enabling shortage risk to vary with both the state of the system and with dynamic uncertainty estimates, our approach captures the full value of flexibility. This approach treats flexibility as a strategy to achieve performance metrics of interest, such as cost and reliability, rather than an end goal itself. This provides more directly useful information to planners who must decide whether upfront investments in flexibility are worthwhile. Future extensions to other applications which have differences in degree and nature of uncertainty, hydrological sensitivity to climate change, and infrastructure alternatives available are likely to have different value of flexibility. This approach can enable planners in these unique settings to assess what types of flexibility if any should be pursued proactively.

Using SDP in combination with EOA enables us to both develop policies for exercising flexible alternatives and evaluate those alternatives using a simulation model. We acknowledge that SDP has limitations for real world planning applications due to its computational expense, which scales exponentially with the size of the problem. In our application, however, the state space is comprised only of long-term climate variables and infrastructure capacity, limiting the size of the problem. To embed the performance using high-fidelity physical models, a hydrological model and infrastructure operation model is run separately for each state in the SDP and the expected value of its performance is saved and used to characterize the SDP cost function. Using a differentiated approach in which uncertainties with high learning potential use a multi-stage stochastic planning approach while others are addressed using more computationally efficient methods can further address this concern when additional uncertainties are incorporated. For example, short-term adaptive operations could be incorporated into this framework in the infrastructure operation model without expanding the state space of the SDP. The limitations of expected utility maximization could be addressed through the use of alternative decision criteria such as those developed by McInerney et al. (2012) [103]. Future work could also use a screening model to optimize the choice of the static and flexible alternatives rather than the heuristic approach used to select the alternatives here. Finally, the approach could be extended to address a more comprehensive consideration of multi-objective planning.

Our approach takes advantage of recent developments in assessing the uncertainty in climate change projections. CMIP5 and related model comparison projects have enabled more sophisticated, probabilistic approaches to quantifying climate change uncertainty in ways that recognize that all models do not perform equally in all parts of the world. We adapt the Bayesian uncertainty modeling approach of Smith et al. 2009 [148] to 1) address change in both T and P, 2) update uncertainty based on potential observations in the future, and 3) use change in mean T and P from one 20-year period to the next, rather than absolute T and P, to reflect greater model skill in predicting changes rather than absolute temperature at the regional level. This approach does have limitations. It assumes that GCMs are independent of one another, when in fact some models borrow entire components from other models [156]. Additionally, we are simulating the potential to learn in the future using only models available today; repeating the analysis in 40 years with a broader range of models reflecting the new state of the science may produce larger shifts in CIs. However, this approach is the best available to assess learning in the future, which impacts planning decisions today. It enables a more precise, validated measure of uncertainty in comparison to the democratic approach used by the IPCC.

Our approach addresses only model uncertainty and not emissions uncertainty. This is an important contribution because model uncertainty dominates overall precipitation uncertainty in the long-term [70], and the lack of political influence on model uncertainty and availability of valid statistical approaches makes a statistical rather than scenario-driven approach appropriate. Future work could extend the approach to address emissions uncertainty by repeating the analysis under different RCPs and assessing regret and robustness of each alternative across scenarios. This framework therefore enables a differentiated approach to climate change uncertainty, in which different types of climate uncertainty are addressed with a unique and appropriate modeling approach.

Chapter 6

Discussion

6.1 Methodological contributions

Developing and assessing water supply infrastructure plans requires an integrated approach that addresses many concurrent sources of uncertainty in the natural, built, and human environments and their impacts on infrastructure. This dissertation makes a contribution to the literature on water supply infrastructure planning under uncertainty through the development of a novel planning framework and its application to develop insights about the potential for flexible infrastructure approaches to mitigate uncertainty in three contrasting planning problems. The planning framework makes several methodological contributions, summarized in Table 6.1

First, the planning framework uses and extends existing dimensions of uncertainty that are important for how uncertainty is modeled to classify uncertainties and match them to appropriate uncertainty analysis tools that are integrated into a single analysis. This addresses a tendency in several current approaches to address all uncertainties in the same way. For example, RDM treats all uncertainties as deep uncertainties and relies on scenario-based approaches; this does not take advantage of the full information available that can be used to characterize some uncertainties probabilistically. Similarly, some uncertainties can be substantially updated as more information becomes available, requiring a dynamic approach; others cannot and are therefore more efficiently addressed using Monte Carlo simulation, which takes a static approach to uncertainty.

Second, it addresses uncertainties with high learning potential — or those for which additional information can feasibly be collected presently or in the future to meaningfully

Table 6.1: Key methodological contributions of this dissertation

Contribution	Description
Uncertainty classification	Framework classifies uncertainties according to two dimensions of uncertainty important for modeling and maps them to appropriate uncertainty analysis methods.
Dynamic uncertainty analysis and management	Bayesian inference combined with multi-stage stochastic programming enables planner to assess the potential to learn about uncertainty in the future and develop planning strategies that account for future learning in decision-making today.
Framework to test value of flexibility	Combines engineering options analysis with hydrological modeling to measure value of flexibility as a planning objective
Parameter uncertainty analysis using statistical surrogate	Artificial neural network maps any combination of uncertain parameters to model predictions, enabling computational efficiency necessary to embed in a stochastic dynamic program.
Dynamic climate model uncertainty analysis	Bayesian modeling using CMIP-5 extended to update initial weightings as additional climate observation data becomes available.

update or reduce uncertainty — using a dynamic approach in which the uncertainty associated with a certain state of the system can change over time as more information is collected. These dynamic uncertainty estimates are developed by applying Bayesian inference to climate models and hydrological models. The hydrological state of the system in the planning model is used as a hypothetical, future observation used to develop a posterior distribution for uncertainty that takes advantage of this new information. By using a multi-stage stochastic planning approach which accounts for all possible future states — as well as the probabilities of reaching those states — our approach develops optimal policies for exercising flexible options that takes into account the potential to learn in the future. Together, these elements achieve an integrated infrastructure planning approaches that combines three elements important for assessing infrastructure planning that had not previously been integrated: 1) dynamic assessments of uncertainty using 2) high-fidelity models of the climate and hydrological cycle to 3) assess infrastructure performance and planning.

Finally, the framework uses engineering options analysis in order to assess the value of flexibility in mitigating the impacts of uncertainty. Previous applications of EOA in water supply have addressed demand uncertainties or made simplified assumptions about supply uncertainty [37]. Here, we integrate uncertainty estimates using hydrological models with

EOA to assess the value of flexible planning and design to address hydrological uncertainty. Some recent work has included flexibility as an objective in a planning model [12]; we provide an approach to assess the value of flexibility as a strategy for achieving other planning, rather than assuming it is a worthwhile goal.

The individual applications of this planning make additional methodological contributions, notably in the integration of physical climate and hydrological models into stochastic programs using statistical approaches to overcome computational limitations. Chapter 4 on parameter uncertainty in groundwater in Riyadh, Saudi Arabia develops a statistical surrogate model of a numerical finite-difference groundwater model using an artificial neural network that provides a mapping of any combination of parameters values to predictions of hydraulic head. This enables computationally tractable numerical calculation of a Bayesian posterior distribution for each of value of the state space. While demonstrated on a simple, 2D MODFLOW groundwater model, the flexibility of artificial neural networks, which have been widely applied in hydrological applications, enables extension to more complex groundwater models in the future. This approach could have applications to other engineering systems domains in which complex physical models are needed to appropriately characterize uncertainty in stochastic planning approaches.

In Chapter 5 on model uncertainty in climate change in Mombasa, Kenya, a similar approach is developed to integrate climate uncertainty into a multi-stage stochastic program. However, the key uncertainty addresses is a model uncertainty rather than a parameter uncertainty. Therefore the approach used in Chapter 4 to map uncertain parameter values to predictions using a single model is not appropriate. Instead, we applied Bayesian model averaging across an ensemble of climate model projections. This approach takes advantage of recent advancements in developing probabilistic climate projection using model intercomparison. To our knowledge, it is the first time these probabilistic climate projections have been used to characterize a stochastic program to assess the impacts of climate change uncertainty on water resources planning.

6.2 Cross-application insights

The individual applications addressed in this dissertation provide insights for planners in each region on the potential for flexibility in infrastructure planning and design to mitigate uncertainty in water supply planning; these insights are discussed in each chapter. Some additional insights about flexibility in water supply infrastructure planning can be drawn by looking across the three applications. In all three applications, we find value in flexible planning or design as means to mitigate uncertainty as well as limitations to the value of flexibility in all cases. We can make some observations about factors that drive value in flexibility in water supply planning.

Learning In all cases, we observe that the process of learning about uncertainty over time is useful in exercising flexible options. This is demonstrated by the result that the flexible option is only exercised in a subset of forward simulations. In Melbourne, the flexible option is exercised primarily in scenarios with high demand growth, after high demand growth has been observed in the first planning period (check on details of this). Similarly, in Riyadh and Mombasa, the flexible expansion option is exercised in response to new observation of rapid head drawdown and rapid drying and warming respectively.

Stochastic variability A challenge in the ability of flexible infrastructure planning to mitigate uncertainty is the presence of irreducible stochastic variability. In Melbourne, while the small flexible alternative has clear advantages over the large desalination plant, it does incur more reliability risk as it does not fully mitigate the impacts of multi-year droughts. In Mombasa, similarly, the flexible alternative is able to mitigate the worst reliability outages, but it still incurs substantially more shortage damages than the large robust alternative. This is not the case in Riyadh where stochastic variability does not play a role: the only uncertainty addressed is an information uncertainty. In Riyadh, therefore, the flexible alternative has a nearly identical reliability profile to that of the static build alternative. This is because the expansion policy derived by the SDP is effective in making sure short-term reliability outages do not occur in the two years between when the decision is made and the capacity comes online — and because there is no variability in supply or demand.

Value of reliability The value of reliability, operationalized in this dissertation as a penalty incurred for water shortages in which demand targets are not met, may or may not have a large impact on the value of flexibility. In the Melbourne application, the shortage penalty is treated as a deep uncertainty and addressed with scenario analysis. The results show that the value of flexibility is highly dependent on this value. In the base case of 25

$\$/m^3$ the flexible alternative performs well. However, when the shortage value is lowered to 5 $\$/m^3$ or raised above 50 $\$/m^3$, the no-build alternative and large plant alternative respectively perform more favorably. In Riyadh, however, the value of flexibility is insensitive to the shortage value. This is related to lack of stochastic variability as discussed above; the flexible alternative almost never incurs shortage damages, and even a most shortage value of $\$5/m^3$, down from the base case of $\$25/m^3$ based on World Bank estimates of water productivity, is enough to promote the flexible alternative over the no-build alternative. In Mombasa, the value of flexibility is also insensitive to the shortage penalty. This is because of the substantially lower capital costs, such that total cost of the large dam is equal to 6.6 MCM of water shortages at the base shortage value of $\$15/m^3$. This means that the optimal SDP policy is incentivized to avoid even small reliability outages. The value of reliability therefore can have a large or modest impact on the value of flexibility, depending on the cost of the infrastructure and the probability of reliability outages.

Discounting We also find a large influence of the discount rate on the value of flexibility. Higher discount rates incentivize delayed capital investments and therefore promote flexible options that defer some or all of the capacity until later time periods. In the applications in Melbourne and Riyadh, we found high value of flexibility across all discount rate values tested. In Mombasa, however, in the scenario based on current demand in which only a dam is built, rather than a dam plus a desalination plant, we find that the flexible alternative has little value without a discount rate.

Economies of scale A key advantage of large, traditional infrastructure project is ability to leverage economies of scale; the unit cost of capacity decreases as the size of the project increases. Modular infrastructure projects, in which smaller volumes of capacity are added as needed, therefore poses a tradeoff between the ability to adapt and the inability to access economies of scale. In Mombasa, the key reason that the flexible dam design has limited value of flexibility in comparison to the large, robust dam is because of the high economies of scale for an earth dam: the large dam is only 27% more expensive for 50% more capacity. The economies of scale for reverse osmosis desalination, however, are much lower because the technology is inherently modular. Therefore, the applications focused on desalination planning rather than dam design faced a much more modest tradeoff. This suggests that water planners choosing between different water supply technology options may want to consider the economies of scale each option faces and whether the technology can effectively take advantage of flexibility.

Type of flexibility The types of flexibility addressed in the applications varies. Chapter 4 evaluates a flexible infrastructure *planning* process in which the *timing* of capacity additions is flexible, while Chapters 3 and 5 assess flexible infrastructure *design* in which the *volume* of capacity additions is flexible. These were chosen to appropriately manage the uncertainties in each case. In the aquifer depletion problem in Chapter 4, it is known that new infrastructure will have to be developed — the question is when. By contrast, in Chapters 3 and 5, it is assumed that new capacity is needed immediately — the question is how much. The specific formulation of flexibility impacts its value. For example, the essential element for success of the flexibility in Chapter 4 is advance preparations, such as choosing a design and location in advance, such that the infrastructure can be brought online in only two years. This makes the risk of reliability much lower. The ability of planners to effectively prepare in advance, enabling them to execute flexible policies quickly and nimbly will have a substantial impact on the potential for flexible approaches to reduce cost risk without impacting reliability.

6.3 Limitations and extensions

Many opportunities exist to improve and extend the approach to flexible water supply infrastructure planning developed in this dissertation. Areas for future work include: the planning framework, planning applications, water resource modeling, social and institutional analysis and other domains. Key opportunities for extensions in each of these areas are summarized in Table 6.2.

Planning framework The planning framework makes a contribution in classifying uncertainties and linking them to appropriate uncertainty analysis tools. There are opportunities to further develop other dimensions of uncertainty and to refine the operationalization of the existing categories. Many dimensions and taxonomies of uncertainty exist beyond those discussed in this dissertation; future work could build theory around which dimensions of uncertainty are important for modeling and managing uncertainty, and whether disagreements on this topic in the literature are based on subjective choices or logical errors [116].

Table 6.2: Key opportunities for extensions and future work

Category	Extension opportunities
Planning framework	Refine operationalization of uncertainty dimensions Test additional uncertainty management strategies Add additional uncertainties and categories as needed
Planning applications	Optimize value of flexibility Improve multi-objective analysis Scale to large systems via integration with simulation-based optimization approaches
Water resource modeling	Identify properties of water systems that drive value of flexibility Extend to other water resources planning problems e.g. hydropower, irrigation, thermal cooling, and flooding Address additional measures of climate change beyond long-term mean T and P e.g. extreme events, autocorrelation, variance
Social and institutional analysis	Use multi-agent modeling to address coupled interactions of planners, stakeholders, and end users Integrate stakeholder collaboration to identify and evaluate uncertainties and opportunities for social learning
Other domains	Extend to other engineering systems infrastructure domains e.g. electricity, transportation Guide and evaluation water technology development

There is substantial debate in the community as to what constitutes deep uncertainty, for example. Further work could explore literature in information theory or the philosophy of science on interpretations of probability to build logical arguments supporting a specific definition.

Opportunities exist to expand on and refine the "learning potential" dimension of uncertainty in future work. In this dissertation, we address only statistical uncertainties with high learning potential and used Bayesian inference to model the potential for future observations to update or reduce uncertainties. In reality, deep uncertainties can present opportunities for learning as well. For example, scenario or emissions uncertainty in climate change is a one of the most commonly cited deep uncertainties, and our understanding of it will certainty change and update over time. Scenario-based approaches for modeling the impacts of this learning process could better enable evaluation of adaptive infrastructure and management approaches to mitigating climate change uncertainty. Additionally, a limitation of the current implementation for statistical uncertainties is that they use only the existing models that are currently available; learning in the future may take the form of new model development.

Additionally, while the framework currently provides a means to test the value of flexibility in managing uncertainty through the use of engineering options analysis, it could be expanded to address other strategies for managing uncertainty as well. For example, information collection could be addressed as a decision variable in which planners can seek out additional information upfront rather than passively collecting it over time. Remotely-sensed earth observation data, such as NASA satellite missions GRACE and its follow on mission GRACE-FO as well as SMAP, present opportunities for new sources of information to reduce hydrological uncertainties in planning decisions.

Planning applications There are a number of practical opportunities to improve the ability of the framework to realistically model planning decisions. For example, further computational advancements may be needed in order to include several high learning potential uncertainties in a single analysis. Additionally, in this dissertation we have not attempted to optimize the choice of static and flexible alternatives; we use the SDP to develop the optimal policy for exercising the option but not the best choice of flexibility. Instead, we have relied on planner-suggested alternatives and heuristic approaches to choose the alternatives to compare. In practice, the specific choices of static and flexible alternative influences the relative value of flexibility. Future work could use screening models [11] or other optimization approaches to compare optimal static and flexible alternatives rather than heuristic-based alternatives.

Future work could also consider a wider range of infrastructure or other planning alternatives. For example, Chapter 4 in Saudi Arabia only evaluated a RO desalination plant. However, wastewater treatment for reuse and additional groundwater development could also be used to increase supply capacity. Across all the applications, demand-side measures to reduce water use through restrictions and incentives could be considered as an alternative to infrastructure development. Effective demand reduction measures are likely to play an important role as uncertainty increases in many water resource systems as a method to manage uncertainty. Integrating demand reduction into the planning framework would require the addition of economic models to asses the impact of — and uncertainty in — human responses to demand policies such as increased tariffs. This could leverage recent work integrating agent-based models into water resource system models to assess social responses to different policies.

Finally, we have only considered two planning objectives in these applications: reliability and cost. Planners have many other objectives as well, such as maintaining ecosystem services, equitable distribution and access, water quality, etc. One notable objective not addressed in this dissertation is the energy intensity of water supply; this is especially important in evaluating desalination investments which are highly energy intensive. Saudi Arabia is aiming to reduce the amount of its energy resource consumed domestically, and evaluating the energy intensity of new investments options is likely to promote options such as wastewater reuse with lower energy use. In order to implement this — as well as the proposed extensions to address a larger number of alternatives in larger scale systems — future work could explore the use of multi-objective evolutionary algorithms [136]. These and other search algorithms that enable simulation-based optimization have been widely used to find Pareto optimal solutions across many planning objectives in large-scale systems more tractably that traditional optimization approaches.

Water resource modeling Future work can also extend the approaches developed here to integrate more complex hydrological models. Groundwater applications can include spatial heterogeneity — a different form of stochastic variability that exists in space rather than time — using a zonal approach. The ANN could be applied using additional input parameters for each of the zones. The ANN could also be used to predict head in multiple wells, which could help identify the shape of the cone of depression and potentially reduce parameter uncertainty more quickly. Additional extensions could apply to unconfined, renewable aquifers with seasonal variation and greater interaction with surface water. This poses a challenge to the assumption of path independence because hydraulic head would not be monotonically decreasing; new planning model formulations could take a hierarchical approach in which annual and seasonal variations are addressed as separate state variables.

The Bayesian climate modeling could also be extended to address uncertain climate variables beyond decadal mean temperature and precipitation. Water planning decisions are also impacted by changes in monthly and annual autocorrelation (e.g. to assess changes in the frequency of multi-year droughts) and variance in T and P. The Bayesian methods developed here could be extended to develop uncertainty estimates for these additional climate metrics and integrated into new stochastic weather generation approaches.

While this dissertation focuses on water supply planning, the planning framework could be applied to other planning questions in water resources. For example, in dam design for hydropower, we could evaluate the potential to learn about electricity demand over time and assess the value of flexible design. Similar extensions could be made in water use for thermal electric cooling and irrigation. The climate analysis could be extended to assess learning about the frequency of extreme events and used to inform flood planning decisions. Similarly, uncertainty in ecological indicators, such as the frequency and duration of low environmental flows, could be incorporated. Long-term future work could aim to integrate these water resources domains to assess learning and flexibility in an integrated water resources management approach.

Finally, application of this method across many different water systems could enable identification of properties of water systems which enable high value of flexibility. For example, the results from the three applications in this dissertation suggest that the relative influence of stochastic variability vs. information uncertainty has a strong influence on the value of flexibility. Designing a large-N study across many water systems could identify and test metrics like the ratio of stochastic variability to information uncertainty to see if they have statistically significant impacts on the value of flexibility. Different regions of the world face different ratios of internal variability, model uncertainty, and emissions uncertainty in climate change [69]. Testing the influence of these different types of uncertainty could enable the development of heuristics that identify systems where flexibility can be applied vs. systems where a robust approach is more favorable. This could be helpful for planners to identify and screen different climate adaptation scenarios without undertaking the full application of this modeling framework.

Social and institutional analysis There are a number of opportunities to extend the framework to address social and institutional uncertainties more comprehensively. First, in our current applications, we have modeled decisions from the perspective of a single planner, focusing on pragmatic alternatives the planner has the authority to implement. In reality, many different actors interact with water resource systems, and decisions made by the planner can influence the behavior of other actors and vice versa. Future work could explicitly model the behavior and decisions of multiple actors to include this two-way coupling of natural and human systems [147]. For small numbers of actors, such as multiple water utilities or planners in a region, game theoretic approaches for managing uncertainty could be used. Alternatively, we could model the impact of many individual actors through agent-based modeling, which has been applied to water resource systems to model the response of individual actors to changes in the water system at different scales [145]. This approach could be extended to address uncertainty by including variability in social responses using statistical or scenario-based approaches. For example, agent-based models could include uncertainty in the impact of demand-side restrictions or policies to reduce water use.

Second, institutional uncertainties could be addressed and included in the uncertainty framework. For example, project delays are a common and impactful uncertainty in infrastructure planning. Indeed, the Wonthaggi plant in Melbourne discussed in Chapter 3 faced lengthy construction delays. This could be included in the existing uncertainty framework by using historical data on construction times to develop probabilistic estimates of project completion time that could be included as statistical uncertainties. In the SDP model, this could be implemented by including probabilistic state transitions for planned infrastructure capacity, instead of assuming a fixed time for project construction. Other institutional uncertainties may require greater extension of the existing uncertainty framework. For example, the deep uncertainty analysis could be extended to identify and address institutional uncertainties that arise from ambiguity, or differences in stakeholder perspective, in a differentiated way. This could draw on recent literature integrating qualitative approaches into engineering systems analysis [154]. For example, qualitative scenario-discovery methods have been applied to identify deep uncertainties in multi-stakeholder decision processes [85]. Mixed-method approaches could be used to elicit the incentives, constraints, and uncertainties impacting the decisions of different stakeholders and then included in the optimization model; recent work has developed and applied this approach in electricity system planning [32].

Finally, future work could integrate stakeholder collaboration, an important element in crafting decision support for planners and policymakers that is directly usable [28]. A key motivation for the differentiated approach to diverse uncertainties developed in this dissertation is that in practice planners face many uncertainties in a single decision. Collaborative or participatory approaches could be used to identify these uncertainties and to classify them in a manner informed by stakeholders' assessment of the level of uncertainty and opportunities to learn in the future. Similarly, prior work in adaptive management has addressed the importance of social learning, in which exchanges across stakeholders and actors lead to greater understanding of the systems [163]. The approach developed here for assessing opportunities to learn about hydrological uncertainty in future could be extended to address social learning processes and its implications for planning decisions.

Other domains Finally, the methods and approaches developed in this dissertation could inform other fields of research as well. Many other engineering systems domains, such as electricity or transportation systems, address infrastructure planning decisions in the face of multiple, diverse uncertainties. The framework presented here could be broadly adapted to those systems. In particular, climate change uncertainty impacts many of these domains and the Bayesian approach developed in Chapter 5 could be applied to other infrastructure systems whose performance is impacted by climate to assess the value of flexible approaches to managing risk. The insights in this dissertation can also guide water technology development. For example, while much of research in desalination aims at improving efficiency and reducing cost of large scale technologies, we demonstrate that modular designs in which smaller volumes of capacity can be added even if the unit cost is somewhat higher can add value at a broader system-level scale. The framework developed here can be used to assess the impacts of new desalination or other water technology developments on water resource systems planning and performance.

Appendix A

Multiple uncertainties in Melbourne

Reservoir operations

For each generated simulation of future natural water supply, we calculate the total urban demand, demand for water from supply infrastructure systems (desalination plants and irrigation pipelines) and the unmet demand on an annual basis.

Total demand is modeled as a product of demand per capita and population. The base population in 2007 is 3.86 million. Each year, population grows at either a high or low growth rate of 150,000 or 50,000 respectively, based on historical data and forecasts [10]. The choice of the high or low growth rate is simulated in each 10-year planning period of the total 30-year model horizon. The probability of high growth is 0.5 in the first period. Condition probabilities are used to model mean reversion; if population growth was high in the first period, it has only 0.25 probability of being high again in the second period, and vice versa. This leads to 8 population growth outcomes, which range from 150,000 to 450,000 in growth over the 30-year planning period.

Once total demand is calculated, the demand from each infrastructure component and unmet demand is calculated using a water balance approach and simple operational rules, represented in Figure C-3 with parameter assumptions shown in Table A.1. The model uses five operational rules to track reservoir storage, water supplied and shortages:

1. Reservoir storage is calculated by adding the natural water inflow is added to the amount of water in reservoirs at the beginning of a given year .

2. Demand is calculated as the demand per capita times the population. Demand is then

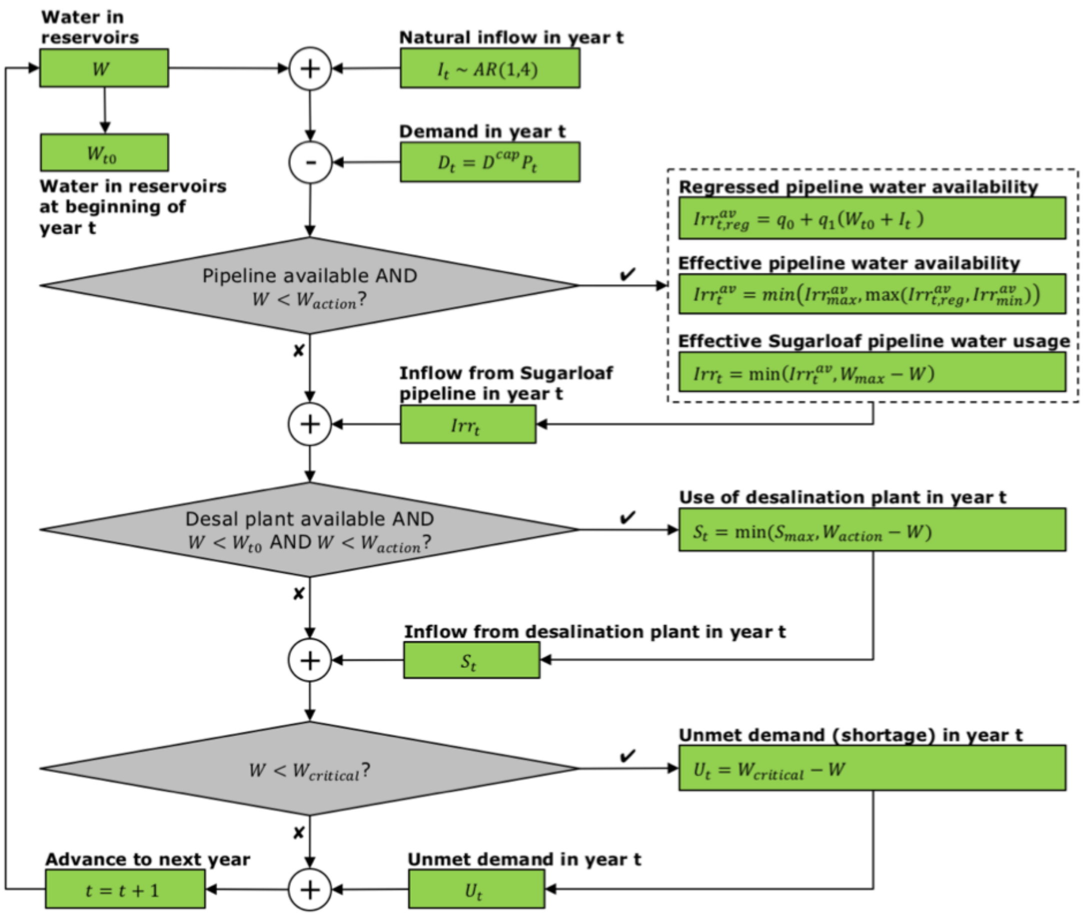

Figure A-1: Schematic showing operational rules assumed in Melbourne analysis subtracted from total reservoir storage, leaving either remaining demand or surplus water availability.

3. If the amount of water left is lower than the action threshold W_{action}, then water from the Sugarloaf pipeline is imported and added to reservoir storage in the infrastructure alternatives in which it is available (S2, S5, and S6). We calculate the amount of water available from the Sugarloaf pipeline as a linear function of the sum of amount of water available at the beginning of year $t(W_{t0})$ and the natural inflow in year $t(I_t)$. This reflects the assumption that the amount of water available from the Sugarloaf pipeline in a given year is correlated with general water availability in the Melbourne area in that year.

4. If reservoir storage is lower than both the action threshold W_{action} and the amount of water at the beginning of year $t(W_{t0})$, then water from the desalination plant is imported and added to reservoir storage, in the infrastructure alternatives in which it is available (S2 – S6). The latter condition reflects the assumption that the desalination plant is only used when the overall water availability is decreasing, and not when the reservoirs are recovering from a drought.

5. Finally, if the water left in the reservoirs after imports from available new infrastructure is lower than the critical threshold, $W_{critical}$. If this is the case, we leave reservoir storage at $W_{critical}$ and register the difference as shortage (unmet demand). This unmet demand would have to be met by sources other than natural inflow, the Sugarloaf pipeline, and the desalination plant, or through demand reductions. Note that the model does not include elastic demand reductions in response to shortages; this approach was taken to be able to simply and clearly measure and communicate the total volume of shortages.

Decision model

We use a decision analysis model to evaluate the six infrastructure alternatives and choose the best in each model run. Population growth uncertainty is incorporated directly into the decision analysis model as an uncertain event to demonstrate the impact of allowing a decision-maker to observe population growth over time and react. In each model run,

Table A.1: Parameter assumptions for water system moel

Parameter	Description	Value	Source/ comment
D^{cap}	Demand per capita	100 kL/p/y	
P_t	Population in year t		Based on population outcome in decision model
q_o	First parameter of regression of Sugarloaf pipeline water availability	-60	Estimate
q_1	Second parameter of regression of Sugarloaf pipeline water availability	0.089	Estimate
Irr^{av}_{min}	Water availability from pipeline during dry years	20 MCM/y	Estimate
Irr^{av}_{max}	Maximum water availability from pipeline	100 MCM/y	Estimate
S_{max}	Desalination plant capacity	75 or 150 MCM/y	Depends on size of plant (small or large) in year t
W_{max}	Maximum capacity of all reservoirs in Melbourne water supply system	1812 MCM	(Melbourne Water, 2015)
W_{action}	Action threshold (of storage level in Melbourne water supply system)	980 MCM	(Melbourne Water, 2015)
$W_{critical}$	Minimum required storage level in Melbourne water supply system	580 MCM	(Melbourne Water, 2015)

perfect information about water supply is assumed, and the choice of best infrastructure alternative is calculated using the standard backward recursion method of solving decision trees [129].

Figure A-2 shows an abbreviated schematic of the decision tree used in this case. In year 0, the decision-maker (DM) chooses from one of the six infrastructure alternatives (S1, S2, ..., S6). Population growth is either high or low over each 10-year planning period, as described in Section A2. Then, after observing whether population growth was high or low, the DM can then decide in year 10 whether to expand the small desalination plant capacity for the infrastructure alternatives that have a small plant with expansion option (S3 and S5). The population growth and planning process occurs again in year 20. We have incorporated a reversion to the mean in the population growth probabilities so that population outcomes tend to be close to the base case over the 30 year planning period; if population growth went up in the previous period, there is only a $\frac{1}{4}$ chance it will go up again in the second period and vice versa. Finally, the population again sees high or low growth until year 30. Each branch of the tree, consisting of a specific outcome of S (the choice of infrastructure alternative), P (the population growth outcome), and O (what expansion option choice was

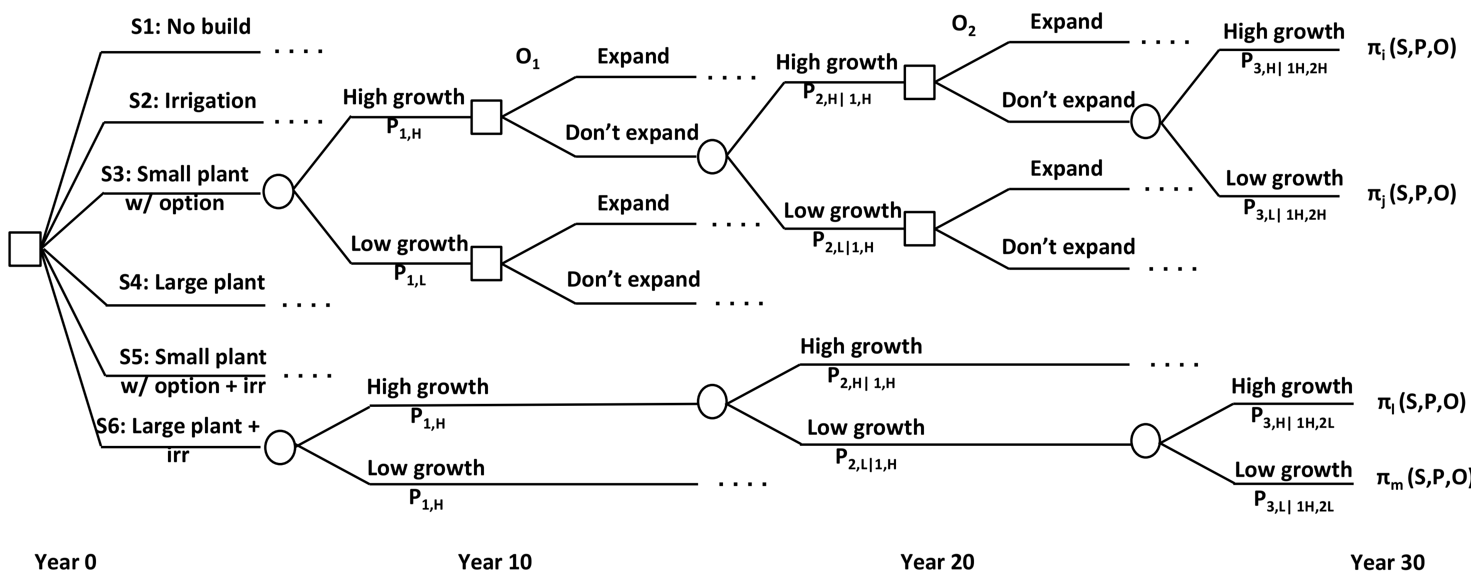

Figure A-2: Abbreviated decision tree illustrating a single run of the decision model. Square nodes represent a choice made by the DM, circular nodes represent an uncertain event outside the control of the DM. Dotted lines represent additional branches of the tree that have been left off for readability.

made), incurs a specific payoff π. For infrastructure alternatives without a flexible expansion option, the DM does not make additional decisions after year 0, and different payoffs are incurred based on high or low population growth in each of the three 10-year periods. The best infrastructure alternative and accompanying expansion option decision (if relevant) are chosen to minimize the expected value of the payoff or total cost function.

Note that the implementation here takes into account path dependence, which is computationally tractable because of the simplified population model which assumes only two possible realizations of population growth in each period. In Chapters 4 and 5, the SDP implementation requires much more granularity in order to incorporate high fidelity physical models of hydrology and climate. Therefore, in those applications, an assumption of path independence is made.

Additional results

Additional results can be found in the Supplemental Information of the published paper, which can be found at: `https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29WR.1943-5452.0000823`

Appendix B

Groundwater uncertainty in Riyadh

Groundwater model

MODFLOW

MODFLOW is a numerical groundwater model developed in the 1980s by the USGS. In this paper, we use the version MODFLOW 2005 [65]. We assume the aquifer is confined and use a 2 dimensional version of the model. MODFLOW therefore solves the following version of the groundwater flow equation:

$$\frac{\partial}{\partial x}\left(K_x \delta \frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(K_y \delta \frac{\partial h}{\partial y}\right) + W(x, y, t) = S\frac{\partial h}{\partial t} \tag{B.1}$$

where K_x and K_y are hydraulic conductivity in the x and y directions respectively, W is the source term in this case reflecting pumping out of the aquifer and recharge into the aquifer, S is the storativity, δ is the aquifer thickness assumed constant, t is time, and h is the hydraulic head.

Artificial Neural Network

400 simulations of the MODFLOW model are used to train the artificial neural network (ANN). Latin hypercube sampling over the prior parameter distribution $p(\theta)$ is used to generate a unique combination of input parameters for each simulation; the set of these parameter combinations span the full possible range. The simulations are run with 100 time steps per year and recorded at a single grid cell representing the Buwayb well field. This yields a total of 4,000 data points for hydraulic head with varying inputs for K, S,

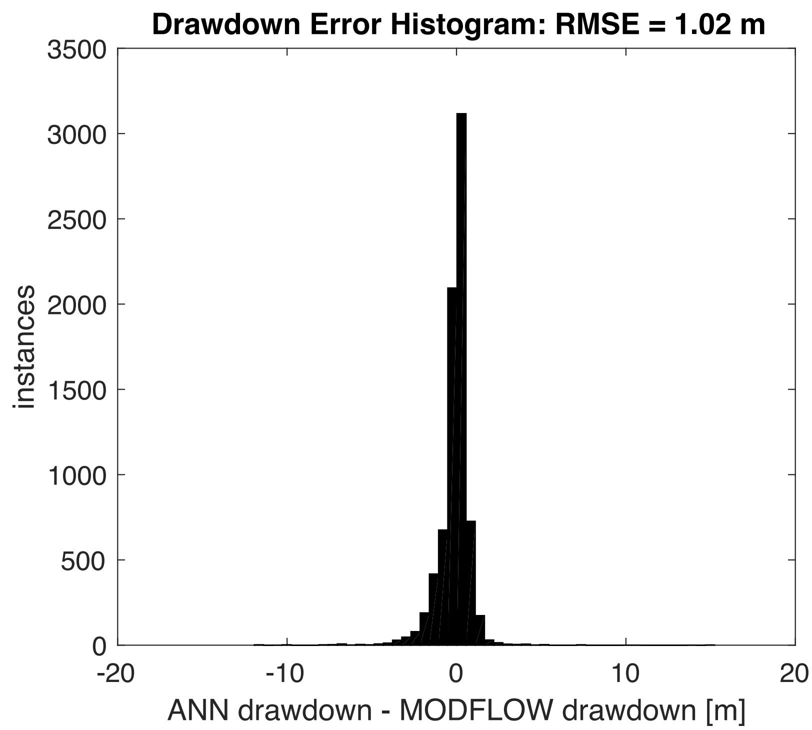

Figure B-1: Error histogram comparing drawdown estimates from MODFLOW to corresponding estimates from the ANN.

and t. This dataset is randomly split into a 70-15-15 train-validation-test partition. A feedforward ANN is trained using MATLAB's scaled conjugate gradient backpropagation algorithm. Many different network architectures varying the transfer function, number of hidden layers, and number of neurons are tested. We select the network with the lowest root mean square error (RMSE) on the test partition. This architecture has 2 hidden layers, with 6 neurons each, and a sigmoid transfer function. Because of the SDP formulation which imposes a drawdown-limit of 50 meters, only observations above the drawdown limit are included in calculating the RMSE; this allows us to choose the model that performs best in the range it will be used in the SDP. The RMSE calculated using this approach is 1.02 m, indicating excellent performance for our long-term regional planning application.

Cost assumptions

Equation 4.4 in Section 4.3 describes the formulation of the SDP for the groundwater application. Figure B-2 illustrates the cost assumptions used in the formulation. The marginal cost of pumped groundwater P is the sum of two components: pumping costs and pretreatment costs because of the brackish quality of the water. Pumping costs were estimated using the cost of energy needed to raise water the height of drawdown in the well plus head losses due to friction estimated using the Darcy-Weisbach equation [77]. Pumping cost range between \$0.40/m^3 at the assumed starting depth of 337 m.a.s.l and \$0.47/m^3 when the 50 m depth limit is reached. Brackish treatment costs were assumed to vary between \$0.3/m^3 and \$0.35/m^3 for the starting depth and maximum depth respectively. The marginal cost of desalinated water is estimated as the sum of pumping costs through an existing pipeline from the desalination plant on the Arabian Gulf to Riyadh plus desalination opex. Pipeline pumping costs are assumed to be \$1.35/m^3 and were estimated as the cost of energy needed to raise water the elevation difference between the desalination plant at sea level and Riyadh at 612 m.a.s.l. plus head losses due to friction again estimated using the Darcy-Weisbach equation [77]; changes in elevation over the pipeline's path were not considered. RO desalination opex and capex were estimated to be \$0.48/m^3 and M\$227 based on a 108 MCM/y capacity plant using the Cost Estimator tool from Global Water Intelligence's "Desal Data" database [56]. This size was chosen to be equivalent to estimated withdrawals from the Minjur aquifer.

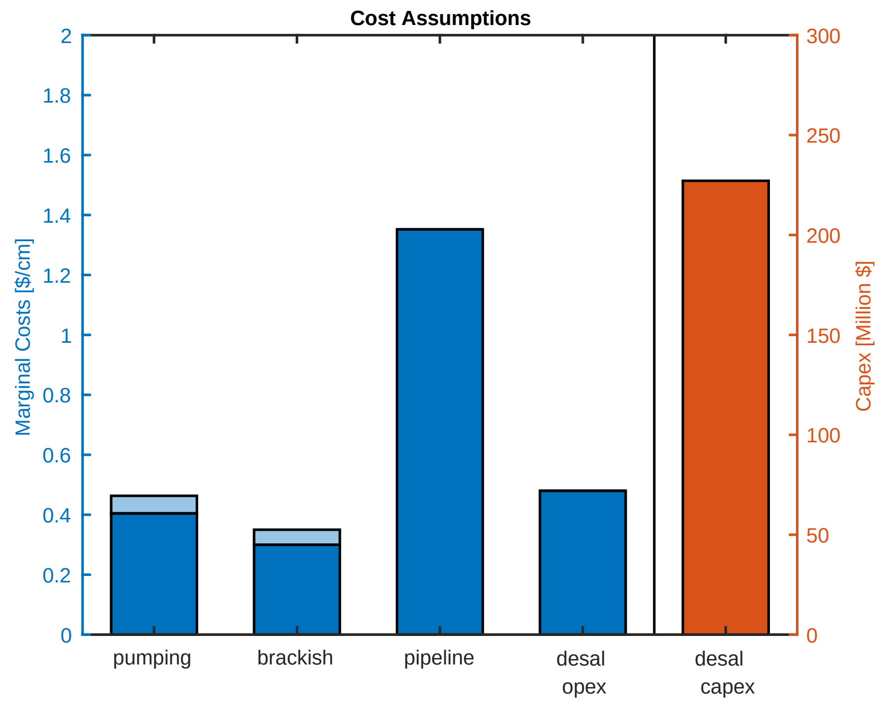

Figure B-2: Cost assumptions for groundwater SDP formulation. Pumping and brackish treatment costs are incurred for water supplied from groundwater; pipeline pumping and desalination opex are incurred for water supplied from desalination. Desalination capex is incurred when a new desalination plant is brought online.

Appendix C

Climate change uncertainty in Mombasa

Bayesian climate uncertainty analysis

An ensemble of 21 climate model projections are used. The models, as well as the ensemble number used, are listed below in Table C.1. More details on the statistical model used can be found in Smith et al. (2009) [148].

K-nn bootstrap for stochastic weather generation

The k-NN bootstrap approach from Rajagopalan and Lall (1999) [132] is implemented as follows:

1. Standardize the GCM's monthly temperature and precipitation values, based on the GCM-monthly climatology over each 20-year time period.

2. Calculate k-value. Because we implement the k-NN based on the climatology of the current month (total of 20 months in the 20 year window) and adjacent months (total of 40 months in the 20 years window), we have a total of 60 months being considered in the nearest neighbor. Following [132], we set k equal to the square root of 60, which we round down to 7.

3. For each value of 20-year mean T and P and time period in the SDP state space, a GCM is sampled.

Table C.1: Climate model ensembles used

Modeling Center	Institute ID	Model Name (ens. member)
Commonwealth Scientific and Industrial ResearchOrganization and Bureau of Meteorology, Australia	CSIRO/BOM	ACCESS 1.0 (1) ACCESS 1.3 (1)
Beijing Climate Center, China, Meteorological Administration	BCC	BCC-CSM1.1 (1)
EC-Earth Consortium	EC-EARTH	EC-EARTH (2, 8, 9, 12)
The First Institute of Oceanography, SOA, China	FIO	FIO-ESM (2, 3)
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3 (1), GFDL-ESM2G (1), GFDL-ESM2M (1)
National Institute of Meteorological Research/Korea, Meteorological Administration	NIMR/KMA	HadGEM2-AO (1)
Met Office Hadley Centre	MOHC	HadGEM2-CC (1)
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	MIROC-ESM-CHEM (1) MIROC-ESM (1)
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine -Earth Science and Technology	MIROC	MIROC5 (1, 2, 3)
Norwegian Climate Centre	NCC	NorESM1-M (1), NorESM1-ME (1)

4. Initialize starting month by randomly selecting a year in sample time window and setting initial current month to January in that year.

5. Calculate the Euclidean distance for all of the current months' and adjacent months' standardized precipitation and temperature values (total of 60 Euclidean distances).

6. Rank the distances from smallest to largest and select the first k ranks $(R_1, R_2, ..., R_k)$.

7. Specify the sampling density, D_i for the first k ranked months as follows:
   $D_i = \frac{1/R_i}{\sum_{j=1}^{k} R_j}$

8. Sample the month from the distribution, D_i and specify the next month in the time series to be the month following the one sampled from D_i.

9. Repeat steps 5-8 using a unique sampling density D_i until the 20-year monthly time series is complete.

10. Transform the standardized monthly time-series back to monthly values by multiplying by the monthly standard deviation, adding the GCM's monthly cycle back in and then adding the annual mean values of T and P. If negative precipitation values exist, set them to zero.

CLIRUN II Rainfall-Runoff Model

CLIRUN II is a lumped watershed rainfall-runoff model designed to assess the impacts of climate change on runoff. It builds on the single layer model CLIRUN [83] by taking a two-layer approach to modeling soil moisture: the upper soil layer and lower groundwater layer allow for both fast and slow runoff response to precipitation [151]. Figure C-1 depicts the model structure and Figure C-2 shows the performance of our model calibration on the Mwache River. More details about the model can be found in Strzepek et al. (2011) [151]

Reservoir Operation Model

The reservoir operation model uses a water mass balance approach, shown in Equation C.1.

$$\Delta S_t = R_t + P_t + D_t - Y_t - E_t - O_t \tag{C.1}$$

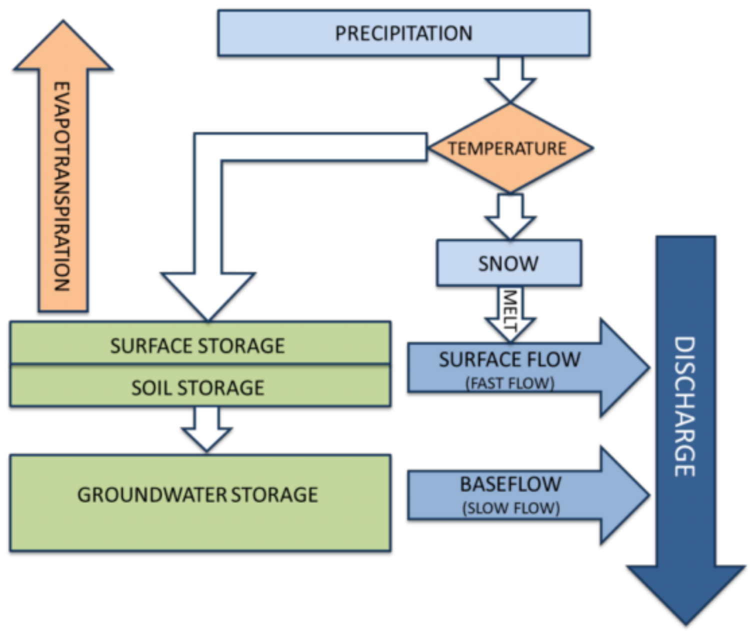

Figure C-1: Schematic depicting structure of CLIRUN II. Model take mass balance of water approach, with six calibrated parameters that determine the flow rates. Reproduced with permission from Strzepek et al. (2011) [151]

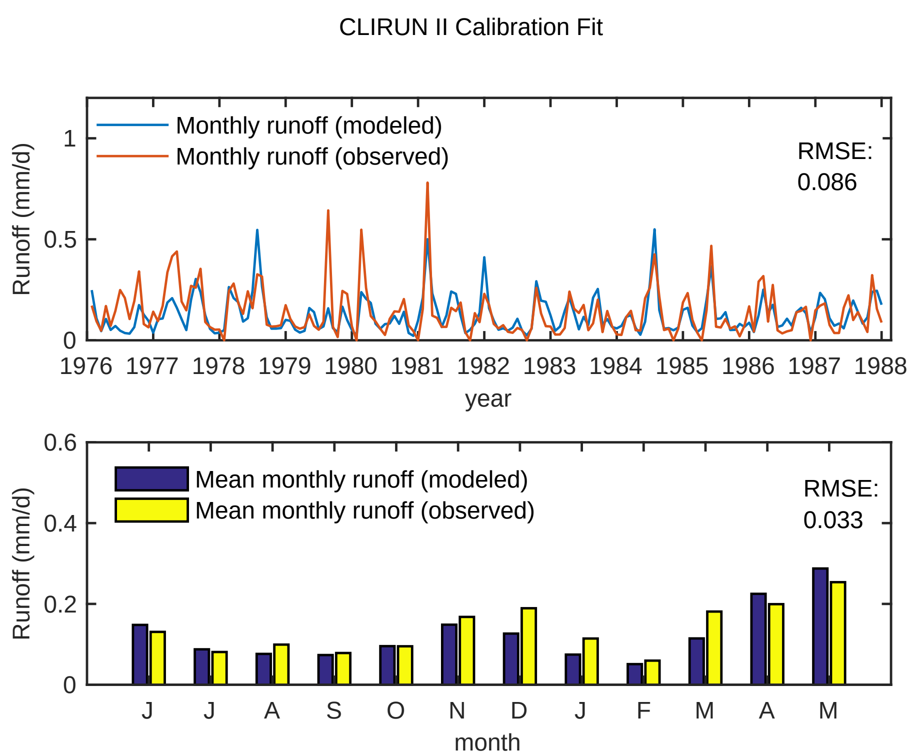

Figure C-2: Calibration fit for CLIRUN II rainfall-runoff model. Top panel compares modeled vs. observed values for monthly runoff from 1976 to 1990. Bottom panel compares modeled vs. observed values for monthly average streamflow across the 14-year time period.

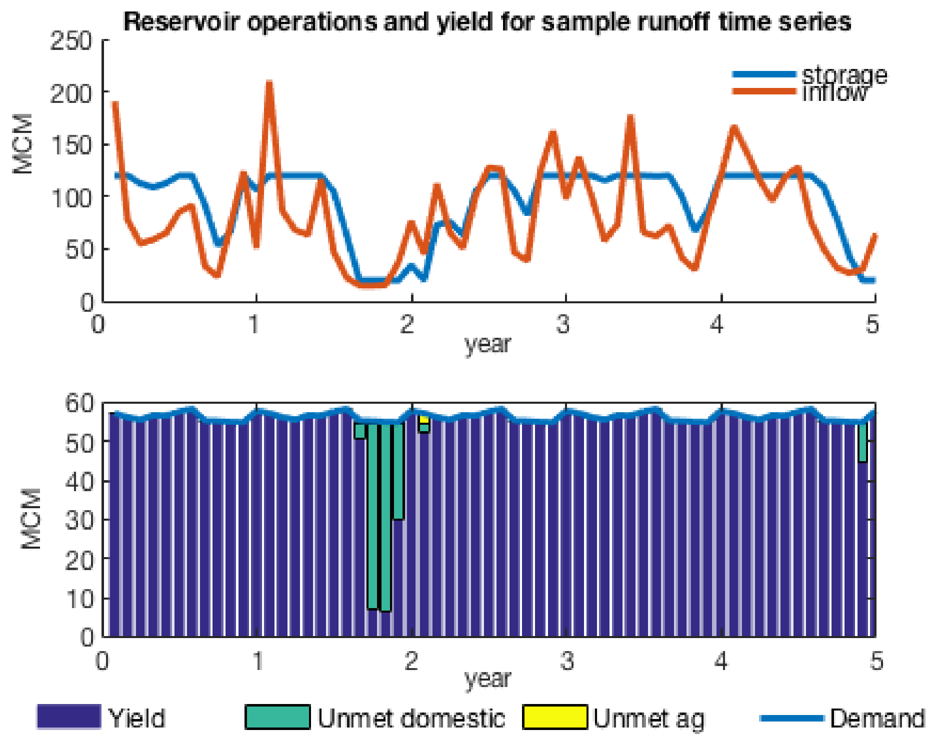

Figure C-3: Reservoir operations model applied to a sample 5-year time series of runoff for a 120 MCM reservoir. Top panel shows reservoir inflows and storage volume. Bottom panel shows yield and unmet demand. In this sample time series, reliability outages occur at the end of year 1 due to several consecutive months of inflows lower than demand.

where S is reservoir storage, R is runoff, P is direct precipitation into the reservoir, D is imported desalination water, Y is reservoir yield delivered to serve demand, E is evaporation from the reservoir estimated using modified Hargreaves [7], O is downstream outflows, and t is time measured in monthly steps. Operating rules are applied such that yields are equal to the full domestic and agricultural demand, or as much as can be delivered. If desalination is available, it is used to refill reservoir storage when storage levels drop below 50% of capacity. Reservoir levels can not drop below the dead storage volume of 20 MCM. Outflows are released to prevent storage going above the reservoir capacity, and we assume no environmental outflow requirements. Figure C-3 demonstrates the reservoir operations for a 120 MCM dam without desalination for a sample 5-year time series of runoff.

Additional Results

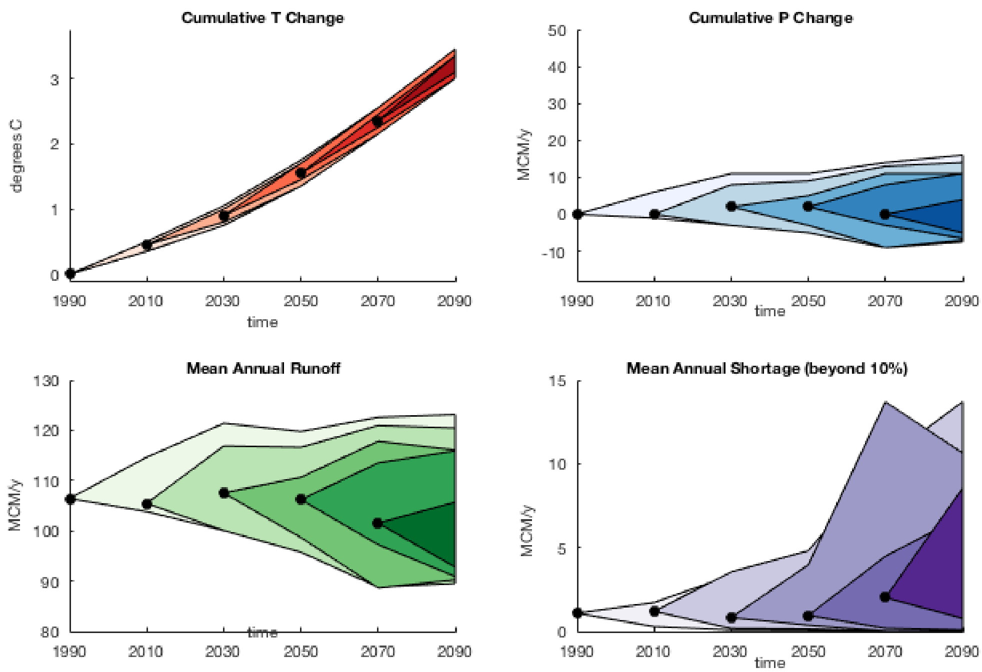

Figure C-4: Confidence intervals for learning over time: alternate simulation in which precipitation and MAR decline, driving shortage risk higher.

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