

Learning about climate change uncertainty enables flexible water infrastructure planning

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Abstract

Water resources planning requires decision-making about infrastructure development under uncertainty in future regional climate conditions. However, uncertainty in climate change projections will evolve over the 100-year lifetime of a dam as new climate observations become available. Flexible strategies in which infrastructure is proactively designed to be changed in the future have the potential to meet water supply needs without expensive over-building. Evaluating tradeoffs between flexible and traditional static planning approaches requires extension of current paradigms for planning under climate change uncertainty which do not assess opportunities to reduce uncertainty in the future. We develop a new planning framework that assesses the potential to learn about regional climate change over time and therefore evaluates the appropriateness of flexible approaches today. We demonstrate it on a reservoir planning problem in Mombasa, Kenya. This approach identifies opportunities to reliably use incremental approaches, enabling adaptation investments to reach more vulnerable communities with fewer resources.

¹ Uncertainty in climate change projections and impacts poses a challenge

2 to infrastructure planning for climate change adaptation [1]. Because of
3 the large expense and widespread need for adaptation investments, planning
4 models play a critical role in targeting available resources. Traditional water
5 infrastructure planning accounts for uncertainty by adding a safety factor to
6 new infrastructure investments[2]. However, these large scale projects are
7 typically irreversible, expensive, and last for multiple decades; the same is
8 true of infrastructure projects in many domains[3]. Preparing for a wide
9 range of future climates by adding extra capacity, therefore, incurs high
10 risk of expensive overbuilding in resource-scare areas. Flexible infrastruc-
11 ture planning has the potential to manage uncertainty at reduced cost by
12 building less infrastructure up front but enabling expansion in the future
13 if needed [2, 4, 5]. Because of the static nature of infrastructure, enabling
14 flexibility often requires substantial proactive planning or upfront investment
15 [6]. In water resources in particular, it is difficult to know whether recent
16 trends in streamflow are a result of climate change or short-term variability
17 and therefore whether they are predictive of future trends [7]. It is there-
18 fore difficult for planners to know if and when to trigger adaptive actions.
19 Short-term reliability outages can occur if infrastructure cannot be adapted
20 quickly [8]. Further, flexibility can ultimately be more expensive if additional
21 capacity is added later by not taking advantage of economies of scale[6]. Ap-
22 propriate methods are therefore needed to weigh the risks and benefits of
23 static vs. flexible infrastructure approaches in responding to climate change
24 uncertainty.

25 Several recent studies provide methods to develop and assess flexible
26 (also called adaptive) infrastructure planning under climate change uncer-
27 tainty. Robust decision making (RDM) uses an iterative scenario develop-
28 ment process to minimize the regret from both overbuilding unnecessary
29 infrastructure and being unprepared for climate change [9, 10, 11]. RDM has
30 been used to develop and evaluate adaptive infrastructure planning strate-
31 gies [12, 13, 14]. New policymaking processes have been developed to design
32 adaptive pathways that allow planners to switch from one action to another
33 if specified thresholds are reached [15] and can be combined with optimiza-
34 tion approaches to identify adaptive thresholds and actions [16]. Recent
35 approaches have provided methods for adaptive sequencing of infrastruc-
36 ture investments [8]. Finally, advances in search algorithms [17, 18] have
37 enabled assessment of adaptive and cooperative approaches against many
38 performance measures using ensembles of General Circulation Model (GCM,
39 i.e. climate model)-driven streamflow projections [19].

40 Adaptive management requires an ability to learn over time as more in-
41 formation is collected [5]. A challenge faced by the above approaches is the
42 difficulty in assessing opportunities to learn in the future. GCM projections
43 provide us with the best available estimates of how the global climate system
44 will evolve under a given emissions scenario. However, as time passes and
45 new climate observations are available, some GCM trajectories will prove to
46 be more reliable than others. For example, suppose current regional projec-
47 tions estimate a range between 0.5 and 1.5 °C of change over the next 20
48 years. If after 20 years we observe 1.5 °C of change, this suggests the climate
49 is warming in this region more rapidly than expected. We may now shift
50 our projections of change upward for the following 20 years. While exist-
51 ing frameworks provide a dynamic, iterative process for planners to change
52 course in the future, they do not provide an upfront assessment of the oppor-
53 tunity to learn about climate change in the future. This upfront assessment
54 is critical to deciding upfront whether investments in flexibility are worth-
55 while or whether a traditional static approach is more appropriate. Existing
56 flexible approaches either assume a priori that flexibility is needed [8], assume
57 perfect information about the future [20], or rely on thresholds or signposts
58 that are unrelated to learning about climate change [21]. None of these
59 approaches provide a mechanism for assessing opportunities to learn about
60 climate change in the future, even though learning about climate change is
61 what triggers flexible decisions. Recent studies have incorporated learning
62 feedback from short-term nonstationary streamflow, but not long-term cli-
63 mate change [22, 23, 14]. Note that while this study focuses on water supply
64 infrastructure, the challenge of characterizing learning about climate uncer-
65 tainty to enable adaptive planning has been highlighted in a range of other
66 disciplines (see, for example [24] in forest management).

67 We develop a planning framework, illustrated in Figure 1, that explic-
68 itly models the potential to learn about climate uncertainty over time and
69 uses potential learning to develop and evaluate flexible planning strategies
70 in comparison to static approaches. First, we use GCM projections forced
71 by a high emissions scenario (Representative Concentration Pathway 8.5)
72 to develop a wide range of possible future mean regional temperature (T)
73 and precipitation (P) outcomes over a planning horizon. We finely discretize
74 mean annual T and P within that range. This develops a comprehensive set
75 of "virtual climate observations" of mean T and P that reflect many possi-
76 ble future regional climates, some of which are drier and some of which
77 are wetter. Next, we use a Bayesian statistical model adapted from [25] to

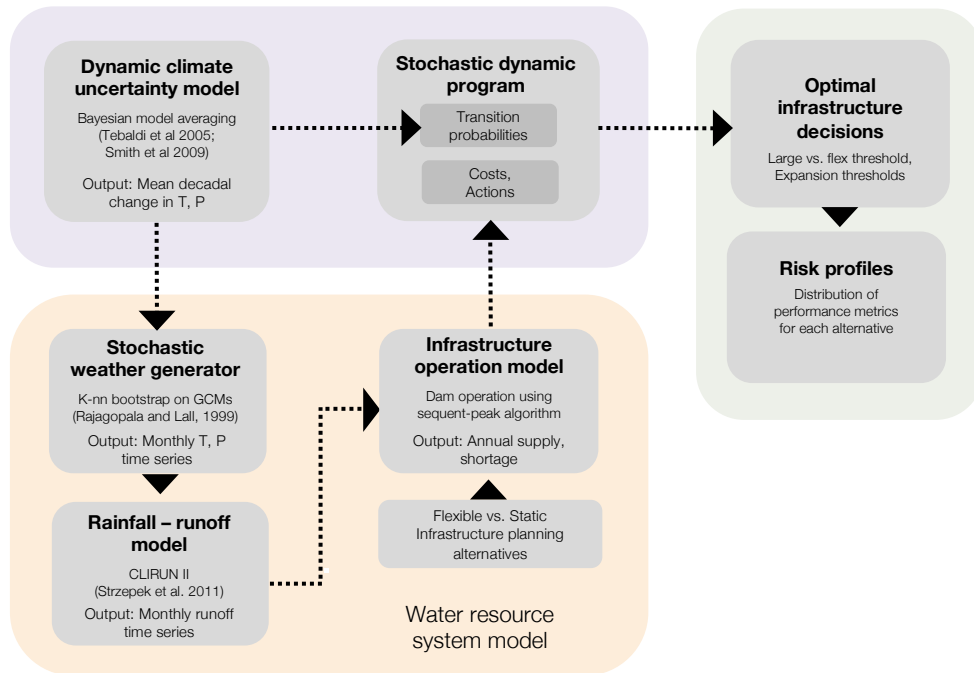


Figure 1: Schematic of integrated modeling framework. Top: Full planning framework. Bottom: Detail on characterizing transition probabilities using Bayesian statistical model applied to each virtual climate observation.

78 update initial climate uncertainty estimates for each virtual climate observa-
79 tion. The updated estimates reflect what we will have learned if the virtual
80 observation comes to pass. These updated uncertainty estimates characterize
81 the transition probabilities in a non-stationary stochastic dynamic program
82 (SDP); each possible in SDP climate state is equivalent to a virtual climate
83 observation. This SDP planning formulation therefore takes into account all
84 the potential new information that may be learned in the future as it de-
85 velops optimal planning policies. We use these polices to evaluate flexible
86 infrastructure planning approaches and compare them to static approaches.
87 See Methods for details.

88 While we do not know today what observations we will see in the future,
89 we can develop policies today for what we will do if a certain observation
90 comes to pass in the future. As an everyday analogy, say we are planning to
91 host a party next week. Our friends are slow to respond to our invitation,
92 and we do not yet know how many people will attend. Therefore, we do not
93 know if our current supply of drinks is sufficient. If we make a final decision
94 today about whether to buy more drinks, we risk unhappy guests if our
95 supply is insufficient or overspending if we buy too much. We can, however,
96 calculate the maximum possible number of guests and assess whether our
97 current supply of drinks is sufficient. If it is sufficient in the maximum case,
98 we can go about our week reassured. If it is not, we can make a plan to
99 reevaluate the responses the day before the party and save time in our day
100 to go to the store for more drinks. We will do this if the expected demand
101 for drinks in light of our updated information exceeds our supply, and in
102 fact we can decide today what number of day-ahead guest responses would
103 prompt us to buy more drinks. In this way, we are developing policies for
104 future actions (going to the store; adding water supply capacity) based on
105 the information from virtual future observations (day-ahead guest responses;
106 temperature and precipitation change) in order to determine whether we
107 should build flexibility into our plan today (saving time for a future errand;
108 choosing a flexible dam design).

109 The United Nations Environment Programme estimates that the cost of
110 climate change adaptation investments in the developing world may reach
111 \$500 billion per year by 2050 [26]; the World Bank estimates that the in-
112 frastructure and water sector adaptation costs may be \$28 billion and \$20
113 billion per year respectively [27]. It is therefore essential to target infras-
114 tructure investments efficiently to reach the widest number of vulnerable
115 communities. Flexible planning strategies are designed to react to changing

116 conditions and information quickly without over investment. They are more
117 likely to be promoted under a dynamic planning model that accounts for
118 learning. To the authors' knowledge, this is the first framework that val-
119 ues the ability of flexible approaches to respond to learning, therefore more
120 comprehensively evaluating the tradeoffs of robust and flexible adaptation
121 strategies. This framework shows promise in identifying areas where smaller,
122 flexible infrastructure is reliable vs. those that require a traditional static
123 approach, enabling billions of dollars of potential savings in climate change
124 adaptation investments across civil infrastructure domains.

125

126 Results

127 We demonstrate this planning framework with an application for Mom-
128 basa, Kenya. Mombasa is the second largest city in Kenya with an estimated
129 population of 1.1 million [28]. Urban water demand is currently estimated
130 at 150,000 m³/day and expected to grow to 300,000 m³/day by 2035 [29].
131 Mombasa has a warm, humid climate with average annual precipitation of
132 900 mm/yr and a mean annual temperature of 26°C [30]. Mean annual
133 runoff (MAR) in the nearby Mwache river, the site of a proposed dam, is
134 113 MCM/yr [31]. While GCMs all project warming in the region, there is
135 disagreement on the direction of precipitation change. This creates substan-
136 tial uncertainty in future runoff and therefore the reservoir capacity needed
137 to meet yield targets over its lifetime. We apply our framework to develop
138 and assess a flexible infrastructure design. The flexible design enables extra
139 storage capacity to be added if the initial dam becomes insufficient due to
140 warmer, drier climates.

141 We assess three planning scenarios, described in Table 1, intended to
142 evaluate the sensitivity of our results to social and technological planning
143 assumptions. In the low-demand scenarios (A and B), we assume a tar-
144 get yield of 150,000 m³/day (54.8 MCM/yr) with 90% reliability from the
145 Mwache dam. We evaluate the two dam sizes proposed by the previous World
146 Bank study [20], 80 MCM and 120 MCM, as well as a flexible alternative in
147 which the height of the smaller dam can be raised, increasing the reservoir
148 capacity to 120 MCM. In planning scenario C we assume a target yield of
149 300,000 cubic meters per day (m³/d) (109.6 MCM/y) with 90% reliability
150 over the entire planning horizon, reflecting the potential for rapid demand
151 growth on relatively short timescales based on 2035 projections from [29]. In

Table 1: Key planning scenarios and corresponding infrastructure evaluated. DR = discount rate; RO = reverse osmosis; Capex = capital expenditure.

Planning 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

152 this scenario, the target yield is greater than observed mean annual runoff
 153 in the Mwache river, and therefore the dam cannot meet the target yield in
 154 today’s climate regardless of its size. Therefore, we model the combination
 155 of a 120 MCM dam and a desalination plant that is used to supply demand
 156 when reservoir storage is low. Three desalination alternatives are chosen,
 157 analogous to the dam design alternatives. A low capacity alternative de-
 158 signed to meet reliability targets in the current and expected future climate
 159 with 60 MCM capacity; the large alternative that meets the reliability tar-
 160 gets across all projected future climates with 80 MCM capacity; a flexible
 161 alternative starts with 60 MCM and can be expanded to 80 MCM. Evaluat-
 162 ing this second scenario allows us to compare the value of flexibility across
 163 two technology options, earthen dams and desalination, which have unique
 164 water supply profiles and cost structures.

165

166 Figure 2 a) and b) show historical observed regional annual T and P from
 167 the Climate Research Unit (CRU) [32] as well as individual GCMs’ projected
 168 changes in T and P relative to 1990. 90% confidence intervals (CIs) of GCM
 169 projections are developed using the Bayesian uncertainty approach, assuming
 170 the historical period is prior to 1990, and compared to CIs developed using
 171 a traditional democratic weighting. The Bayesian approach weights models
 172 based on how well they match historical observed changes in T and P (see
 173 Methods). The democratic approach assumes all models perform equally well
 174 [33]. Between these two methods, the Bayesian approach produces smaller
 175 CI because it assigns more weight to a subset of models that best match
 176 historical change in this region.

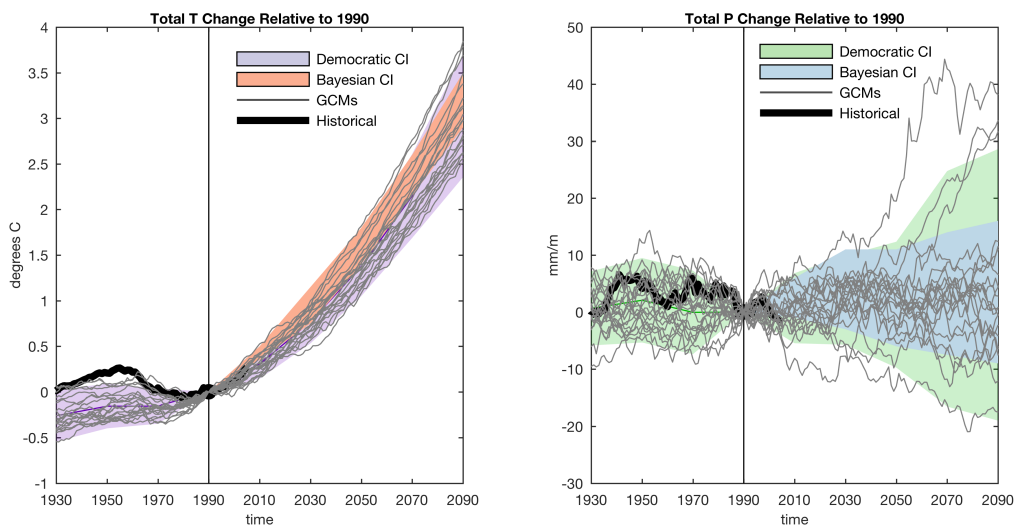


Figure 2: a)(or b)): Modeled and observed temperature (precipitation) relative to 1990 values with uncertainty estimates. Gray lines are 20-year moving averages of GCM simulations over Mombasa. Black lines show the corresponding historical observed values. Purple (green) shaded regions show the 90% CIs using the IPCC democratic weighting method, (i.e. $\pm 1.64 \times \sigma$). Orange (blue) shaded regions show the 90% CI developed using the Bayesian uncertainty method applied to historical regional observations before 1990.

177 While Figure 2 presents Bayesian CIs based on historical observations,
178 the SDP transition probabilities require Bayesian uncertainty estimates that
179 reflect what will have been learned for many possible virtual future obser-
180 vations. We assume that precipitation change will range between -30% and
181 +30% by end of century; we discretize this range at 2% for a total of 31
182 unique virtual precipitation change observations. We apply the Bayesian un-
183 certainty analysis to each of these 31 virtual precipitation change observations
184 in each time period. For example, two sample time series of virtual T and
185 P observations and their corresponding updated uncertainty estimates are
186 shown in Figure 3. An example of strongly increasing P is shown at top; an
187 example of modestly decreasing P is at bottom. For each virtual observation,
188 we simulate 10,000 virtual climate time series from the current observation to
189 the end of the planning period and construct a 90% CI, shown by the shaded
190 regions. This process is repeated for each time step, with darker colors in the
191 plot corresponding to the CIs developed from virtual observations sampled
192 later in the planning period. The darker CIs therefore reflect uncertainty
193 estimates updated with information farther into the future. The sample of
194 virtual observations showing strong increases in P (Figure 3 a-d), leads to
195 high certainty by the end of the century that negligible water shortages will be
196 incurred, assuming the small 80 MCM of dam capacity. Strong asymmetric
197 uncertainty reflects the low-probability, high-severity risk of droughts; short-
198 ages occur only when runoff is substantially below MAR for several months.
199 The alternate sample of virtual observations showing modest decreases in
200 P demonstrates a reduction in uncertainty in both P and *MAR*. Expected
201 water shortages increase substantially as more observations are collected,
202 and the uncertainty increases as well due to non-linear relationships between
203 *MAR* and shortages.

204 While two sample time series of observations are illustrated in Figure
205 3, the SDP optimal strategy accounts for a wide range of possible future
206 observations and what would be learned if they were to be observed. This is
207 achieved through the multistage stochastic optimization formulation, which
208 allows for uncertain, rather than deterministic, transitions to new climate
209 states in each period. In the first time period, shown in Figure 4 (a), the
210 SDP develops a threshold as a function of T and P during the 2001-2020 time
211 period when the initial infrastructure decision is made. Above the threshold,
212 in hotter and drier climates, the large dam is optimal and below it the flexible
213 dam is. Due to the small cost difference between the flexible and large dam,
214 investing in the large dam option upfront is preferred if the risk of shortages

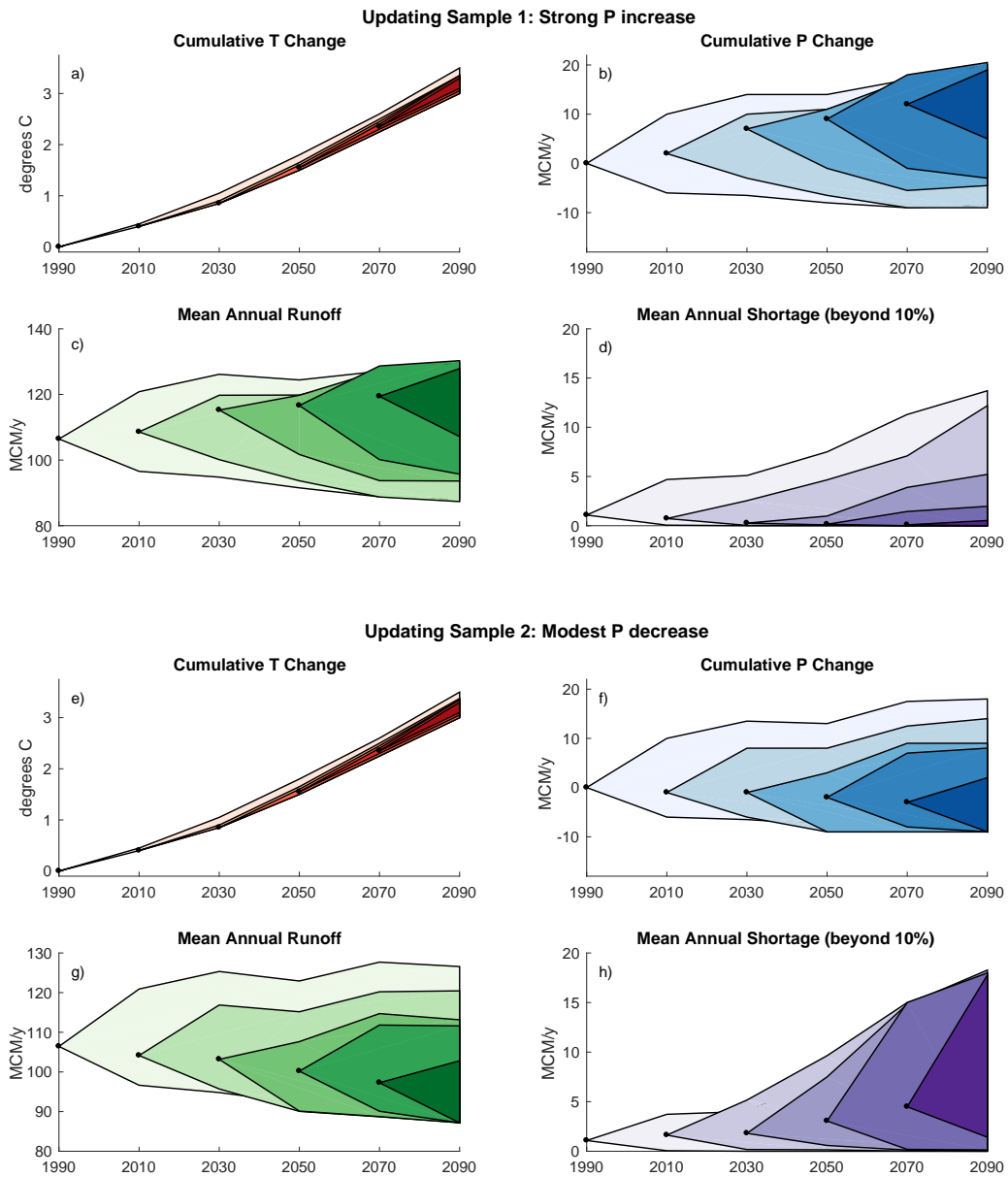


Figure 3: a-d: One sample realization of Bayesian learning over time in which precipitation increases strongly. Black dots represent a time series of virtual climate observations. Shaded regions indicate the projected 90% CI, updated with each time period's virtual observation. Virtual observations of T (a) and P (b) are used to simulate MAR (c), and water shortages assuming 80 MCM dam capacity (d). e-h): As in a-d but for an alternative realization of virtual observations, showing modest decrease in P.

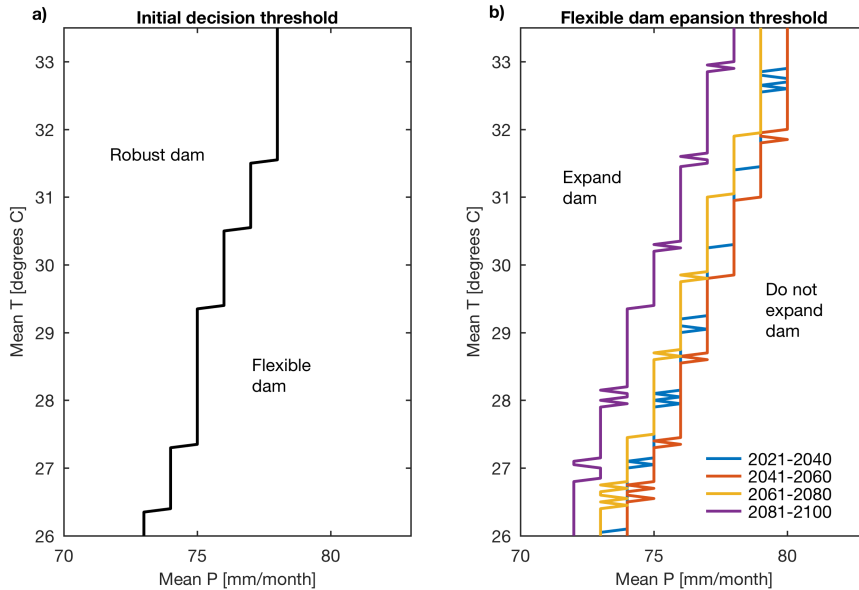


Figure 4: Optimal policies from SDP. a): Threshold for initial decision between large static and flexible design as a function of T and P during the first time period (2000-2020). b): Thresholds for exercising the option to increase height of flexible dam as a function of T and P during the latter time periods as indicated on the legend. Results shown for planning scenario A.

215 at the outset is high enough. This reduces expected costs by leveraging
 216 economies of scale. Panel b) shows expansion thresholds for time periods 2-5
 217 for the flexible dam. Expanding infrastructure capacity is optimal in drier
 218 and warmer states. In the 2041-2060 time period, the policy threshold shifts
 219 right, reflecting the narrowing of uncertainty due to additional information in
 220 later time periods. In later time periods, however, it shifts left, reflecting the
 221 influence of the end of the planning horizon which disincentivizes investment.

222 Figure 5 shows infrastructure decisions under the optimal policy across
 223 1000 simulated climate time series. In planning scenario A, the flexible alter-
 224 native is chosen in 90% of simulations, shown in panel a). When the flexible
 225 alternative is chosen, the option to expand is never chosen in about 90% of
 226 simulations. This highlights the low probability of reaching a climate dry
 227 enough to generate shortages beyond 10% of demand. The time period at
 228 which expansion is exercised varies; more rapid warming and drying leads to
 229 earlier expansion. Panel b) shows cumulative distribution functions (CDFs)

230 of the total cost (including shortage damages) of each alternative across the
231 1000 simulations under planning scenario A. The large static alternative has
232 the same cost across simulations; as designed, no shortage damages are in-
233 curred in any feasible climate. The small dam performs better than the large
234 dam in about 70% of simulations, but has substantially higher costs in 30%
235 of simulations due to large damages from water shortages. The flexible dam
236 mirrors the small dam in 70% of simulations, but the reliability risk is sub-
237 stantially mitigated because of the potential to expand. The high-end costs
238 are higher than the large dam because 1) the cost of building the 80 MCM
239 dam and expanding to 120 MCM is higher than building the 120 MCM dam
240 upfront and 2) sometimes the dam is not expanded even when modest wa-
241 ter shortages are incurred. The ability of the flexible alternative to mitigate
242 both the risk of overbuilding and the risk of severe shortages demonstrates
243 the high value of flexibility in this case.

244 The value of flexibility changes under planning scenarios B (no discount-
245 ing; panels c-d) and C (high demand with desalination plant; panels e-f).
246 Without discounting, the large dam is more favorable; it performs best in
247 60% of simulations, has no cost variability risk, and is chosen in 80% of sim-
248 ulations. Large economies of scale in the dam mean that a 120 MCM dam is
249 only 30% more expensive than an 80 MCM dam for 50% additional capacity.
250 This suggests it is often better to build the large dam upfront even if there
251 is a relatively low probability that it will be needed. Scenario C evaluates
252 a 120 MCM dam combined with a desalination plant. We find a high value
253 of flexibility even without discounting. The flexible alternative is chosen up-
254 front in over 80% of forward simulations. The CDF demonstrates that it
255 outperforms the static alternatives by substantially mitigating the over build
256 risk in comparison to the robust alternative. The flexible alternative also
257 modestly reduces the shortage damage risk in comparison to the small alter-
258 native. While the flexible alternative only reduces cost at the 90th percentile
259 and above, this substantially reduces the expected value as the maximum
260 cost of the small plant reaches almost M\$400.

261 Looking across scenarios, the flexible alternative is chosen most often
262 in scenario A because discounting incentivizes delayed capital investments.
263 This is not the case in scenario B because large economies of scale incentivize
264 a single, large investment. In scenario C more modest economies of scale
265 lead to high value of flexibility in the absence of discounting, highlighting
266 differences in the value of flexibility across technologies. Across all scenarios,
267 the flexible dam is expanded in no more than 10% of simulations, highlighting

Simulated infrastructure decisions and costs (N=1000)

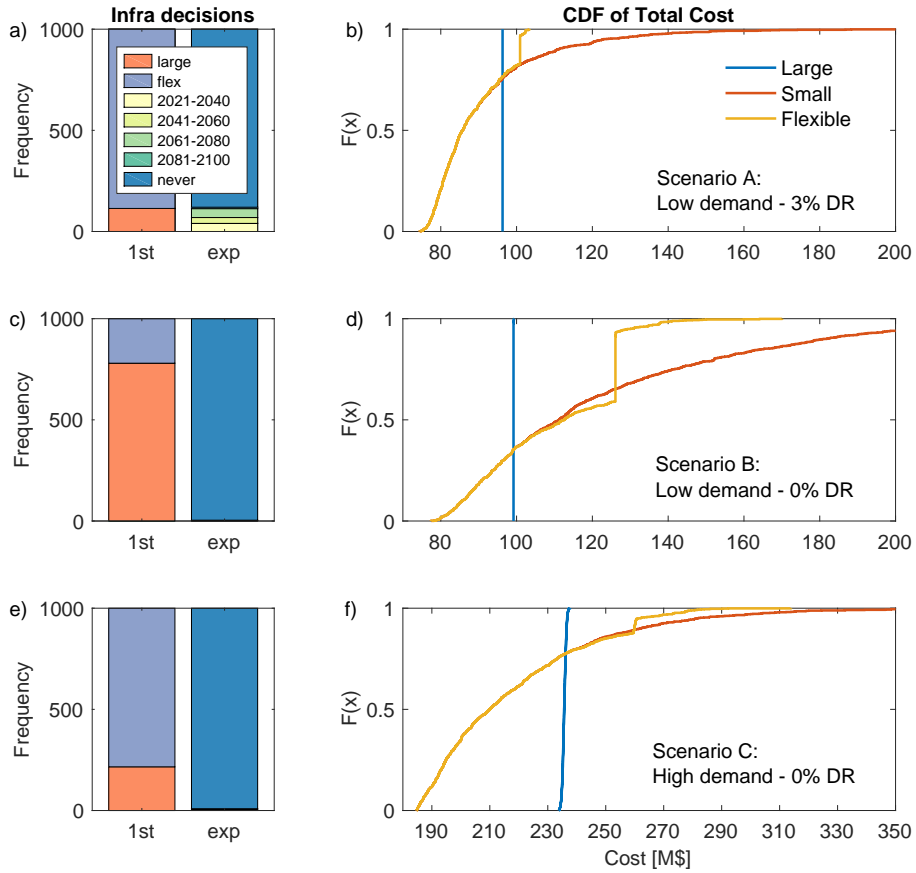


Figure 5: Simulated infrastructure decisions (left) and costs (right). a)-b): planning scenario A (low-demand, discounting). c)-d): planning scenario B (low-demand, no discounting); e)-f): planning scenario C (high-demand, no discounting).

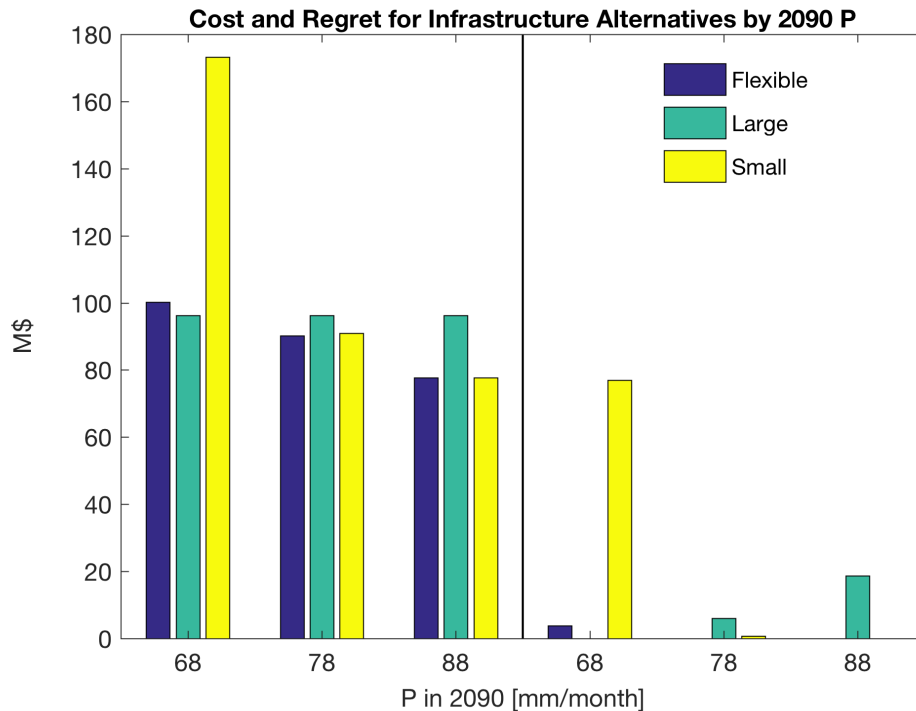


Figure 6: The total cost including shortage penalties (left) and regret (right) of infrastructure alternative in planning scenario A is assessed in three representative end-of-century P values: a dry climate of 68 mm/month, a moderate climate of 78 mm/month, and a wet climate of 88 mm/month.

268 the low probability of reaching a climate that is hot and dry enough to incur
 269 substantial shortages.

270 Finally, while the previous analysis has relied on a "top-down" analy-
 271 sis that uses GCM projections to develop probabilistic forecast, Figure 6
 272 presents an illustrative "bottom-up" analysis that demonstrates the average
 273 cost and regret of each of the three dam alternatives in planning scenario
 274 A under different end-of-century climates without relying on probabilistic
 275 forecasts. Regret is defined as the difference between the cost of the chosen
 276 infrastructure alternative and the best possible infrastructure alternative in a
 277 given climate state. Three illustrative climates are chosen to demonstrate the
 278 tradeoffs across alternatives: a dry climate of 68 mm/month, an moderate
 279 climate of 78 mm/month, and a wet climate of 88 mm/month. Differences in
 280 T are not considered because its impact on water shortages is limited. The

281 small dam without expansion has the highest maximum regret of any alter-
282 native of M\$77, incurred in the dry climate. The large dam incurs positive
283 regret in both the moderate and wet climates, with the latter incurring M\$19
284 of regret. The flexible dam has the lowest maximum regret, with a modest
285 M\$4 of regret in the dry climate. This bottom up approach also highlights
286 the ability of the flexible dam design and expansion strategy to mitigate risk
287 in a range of different potential future climates.

288 1. Discussion

289 We develop a method that integrates iterative Bayesian learning about cli-
290 mate uncertainty into a multi-stage stochastic infrastructure planning model
291 in order to address a critical limitation of adaptive infrastructure planning in
292 both water supply and other domains: estimating upfront how much planners
293 can expect to learn about climate change in the future and therefore whether
294 adaptive approaches are likely to be reliable and cost effective. Our approach
295 quantifies, for example, the extent to which a wet trajectory over the next 20
296 years increases the likelihood of a wet trajectory 40 years into the future. By
297 applying the Bayesian model to a wide range of discrete virtual future climate
298 observations, we develop adaptive policies that take into account all future
299 opportunities for learning. While all approaches that use GCM ensembles
300 face limitations, this approach provides a reasonable quantitative estimate of
301 future learning that enables better-informed assessment of tradeoffs between
302 planning approaches. This allows us to evaluate the effectiveness of flexible
303 planning, which relies on learning processes that remain unquantified in pre-
304 vious methods, rather than assuming a priori that flexibility is a worthwhile
305 planning goal. This is especially important for infrastructure planning where
306 planners must prepare in advance to take a flexible approach due to the large,
307 irreversible nature of infrastructure investments.

308 The results in the Mombasa application demonstrate the nuances and
309 tradeoffs inherent in comparing flexible and robust approaches for planning
310 under climate uncertainty. Although the uncertainty and learning is driven
311 by the climate system, decisions about whether flexibility is a valuable tool
312 in mitigating risk are strongly influenced by social, technological, and eco-
313 nomic factors. The large economies of scale in earthen dams make flexibility
314 less valuable; it is better to choose a robust alternative when it is not much
315 more expensive to do so. Reverse osmosis (RO) desalination, however, is an
316 inherent modular technology with modest economies of scale, lending itself

317 more readily to flexible planning. The discount rate, which trades off future
318 adaptation goals for immediate rewards, promotes flexible approaches. Flex-
319 ibility often delays investment, which can be especially impactful in resource-
320 scarce areas where unused capital could support other critical infrastructure
321 services. The value society places on access to reliable, sustainable water
322 supplies — and the damage of short-term outages — is also influential.

323 Future extensions to other planning problems which have differences in
324 degree and nature of uncertainty, hydrological sensitivity to climate change,
325 and social context can be used to assess under what conditions flexible or
326 static planning approaches are more appropriate. Future work combining this
327 learning approach with bottom-up vulnerability assessments can address the
328 limitations of GCM-based probability distributions [34]. Identifying opportu-
329 nities to learn and adapt flexibly can both enable efficient individual planning
330 decisions as well as target collective climate change adaptation investments
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503 2. Author contributions

504 SF conceptualized the study. SF, ML, and KS designed the methodology.
505 SF and ML performed the analysis. SF and ML wrote the manuscript. SF,
506 ML, and KS edited the manuscript.

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514 **4. Competing interests**

515 The authors declare no competing interests.

516 **5. Materials and Correspondence**

517 Data and code are available from the corresponding author upon rea-
518 sonable request. Correspondence should be addressed to Sarah Fletcher
519 (sfletch@mit.edu).

520 **Methods**

521 This study develops a framework for infrastructure planning under cli-
522 mate change uncertainty that uses Bayesian uncertainty analysis to assess
523 opportunities to learn about climate change uncertainty in the future and
524 therefore evaluate the effectiveness of flexible infrastructure planning. Each
525 component of this analysis is detailed below. We note that the integration
526 of the Bayesian statistical model with the SDP to develop flexible infrastruc-
527 ture is the key methodological contribution and designed to be generalizable
528 to many other domains. However, we demonstrate this on an example from
529 water supply and therefore use a relatively simple water system model (com-
530 prised of the stochastic weather generator and infrastructure operations, de-
531 scribed below) in this particular application. Future applications could tailor
532 the water resource system model to the application at hand.

533 *Bayesian modeling of climate change uncertainty*

534 We extend the Bayesian uncertainty analysis of [25] to characterize the
535 SDP transition probabilities. [35] show that the uncertainty in climate pro-
536 jections due to natural variability remains relatively constant throughout the

537 21st century, but that as the climate signal emerges from the noise, the un-
538 certainty in projections is dominated by the GCMs' climate sensitivity, and
539 hence structure. We therefore limit our focus to uncertainty in model struc-
540 ture rather than emissions or stochasticity 1) because structural uncertainty
541 dominates long-term precipitation uncertainty [35] and 2) to utilize recent
542 statistical methods for characterizing structural climate uncertainty [36, 25].
543 The approach in [25] uses ensembles of projections from the fifth phase of
544 the Coupled Model Intercomparison Project (CMIP5) [37] to derive a single
545 distribution describing uncertainty in climate change. In our approach, fol-
546 lowing [25], we use historical observations or virtual observations to estimate
547 the reliability of each model run and therefore its weight in the resulting prob-
548 ability distribution. This is in contrast to the "democratic" approach used
549 by [38] and Intergovernmental Panel on Climate Change (IPCC) in which
550 each model projection is assumed equally likely and the multi-model mean
551 and standard deviation is used to derive a single probability distribution.

552 We extend the Smith et al. (2009) statistical model in three ways. First,
553 we apply the model to annually averaged P and T values separately, assuming
554 that T and P are independent. This reflects that a model's performance in
555 estimating T may be unrelated to its ability to estimate P. Second, we apply
556 the model to observed and projected change in T and P (i.e. ΔT and $\% \Delta P$)
557 rather than absolute T and P due to greater model skill in GCM projected
558 changes in temperature and precipitation rather than absolute values [39, 40].
559 This is especially important in our application in Mombasa where there is
560 less disagreement in temperature change than there is disagreement in hind-
561 casted absolute temperature.

562 Finally, we apply the model to 1) multiple pairs of time windows and 2)
563 many virtual observations of change in T and percentage change in P. Smith
564 et al. (2009) assumed two periods: a historical climate (1961-1990) and a
565 future climate (2071-2100). We also use a historical and future climate in
566 each estimation of the Bayesian model; however, we define 6 time periods
567 using pairs of adjacent 20-year windows and calculate the change in T and
568 percentage change in P between adjacent windows. This gives a total of 5
569 pairs of historical and future adjacent windows within 1960-2099. In each
570 pair of adjacent windows, the "historical" window corresponds to the cur-
571 rent time period in the SDP and the "future" window corresponds to the
572 next 20-year period; this is necessary for the 1-stage transition probabilities
573 needed in the SDP. The 20-year time interval was chosen so that interannual
574 variability was not driving the trend in precipitation and temperature across

575 time periods. Smith et al. (2009) used historical observations of climate
576 data (X_0 in Equation 1); we repeat the analysis many times using unique
577 virtual climate observations, $\Delta V_{t,i}$, corresponding to changes in the SDP cli-
578 mate states, where t denotes the time period and i denotes an index between
579 1 and N , the possible virtual observations. Virtual temperature change ob-
580 servations range from 0 to 1.5 °C using discrete steps of 0.05 °C ($N=31$).
581 Virtual observations of percentage change in precipitation range from -30%
582 to 30% using discrete steps of 2% ($N=30$). These were chosen in order to be
583 comprehensive of all potential future climate states. Therefore, they must 1)
584 be granular enough that adjacent observations result in similar distributions
585 and therefore approximate a continuous set of observations and 2) span a
586 range that exceeds the full range of change predicted by models (i.e. a range
587 of 0 to 1.5 °C per 20-years is equivalent to 0 to 7.5 °C of change after 100
588 years; the CMIP5 ensemble projections a temperature change in the range
589 of 2 to 4°C by 2100, fitting well within the range resulting from the virtual
590 observations).

591 The evaluation of GCMs' performance in reproducing climate observa-
592 tions will depend on time scale, region, and variable of interest [41, 42].
593 Because our ultimate goal is to update our learning of regional climate in
594 the Mwache catchment with respect to multi-decadal trends in precipitation
595 and temperature, we choose to weight GCMs based on their performance in
596 reproducing multi-decadal trends of precipitation and temperature averaged
597 over the catchment area. Therefore, to implement the Bayesian uncertainty
598 analysis in Mombasa, we use a total of 21 CMIP5 members whose modeling
599 group and model run are included in SI Table 1. The 21 GCM simulations
600 come from 10 different institutions and 15 different GCMs, with three GCMs
601 providing more than one simulation. Models were selected based on the
602 most readily available models at the time of the analysis, with 21 being in
603 line with previous studies, providing a reasonable balance between compu-
604 tational limits and model diversity [43]. All models are forced by the RCP
605 8.5 scenario, which is the high emissions scenario from the IPCC AR5. For
606 each GCM, monthly temperature and precipitation values are averaged over
607 2°S to 6°S and 38°E to 42°E, overlaying the Mwache catchment; GCM pro-
608 jections are regridded from their original resolution following the approach
609 in Boehlert (2015) [44]. These regional temperature and precipitation GCM
610 outputs, rather than global outputs, provide the basis for model weighting
611 in the Bayesian analysis.

Following [25], the statistical model is formulated as follows for ΔT ; an

identical and independent model is used for $\% \Delta P$. The estimate of future change in mean temperature between $t=0$ and $t=1$, ν_1 , is based on historical observed temperature change to $t=0$, X_0 :

$$\begin{aligned} \Delta X_0 &\sim N\left(\mu_0, \lambda_0^{-1}\right) \\ \Delta X_0^j &\sim N\left(\mu_0, \lambda_0^{j-1}\right) \\ \Delta X_1^j | \Delta X_0^j &\sim N\left(\nu_1 + \beta_0 * (\Delta X_0^j - \mu_0), (\theta_0 * \lambda_0^j)^{-1}\right), \end{aligned} \tag{1}$$

612 where ΔX_0 is the historical observed temperature change to $t=0$. ΔX_0^j
613 is model j 's projection of temperature change to $t=0$, and ΔX_1^j is the same
614 for $t=1$. ΔX_0 , ΔX_0^j , and ΔX_1^j are treated as samples from unique normal
615 distributions. μ_0 and ν_1 are random variables representing the underlying
616 distributions of temperature change in the current ($t=0$) and future ($t=1$)
617 time periods respectively. λ_0^j is the inverse variance of ΔX_0^j , representing the
618 reliability of model j . β_0 is a regression parameter that introduces correlation
619 between ΔX_0^j and ΔX_1^j ; it is estimated by the model rather than assumed.
620 θ_0 is also an estimated parameter that enables a model to have different
621 reliability in the future compared to the present. The marginal densities
622 for each of the parameters are estimated using MCMC methods; we use
623 the Gibbs sampling approach, parametric assumptions including priors, and
624 code developed in [25]. The Gibbs sampler collected 1000 samples, discarded
625 the first 150,000 samples as a "burn-in", and saved 1 in every 1500 samples;
626 convergence was checked using standard diagnostics including trace plots and
627 auto-correlation plots.

When $t > 1$, unique estimates of future change in mean temperature from $t-1$ to t , $\nu(\Delta V_{t-1,i}^*)$, are based on each virtual observation of temperature

change from the previous time period, $\Delta V_{t-1,i}$, as follows:

$$\begin{aligned}
\Delta V_{t-1,i} &\sim N\left(\mu(\Delta V_{t-1,i}), \lambda(\Delta V_{t-1,i})^{-1}\right) \\
\Delta X_{t-1}^j &\sim N\left(\mu(\Delta V_{t-1,i}), \lambda^j(\Delta V_{t-1,i})^{-1}\right) \\
\Delta X_t^j | \Delta X_{t-1}^j &\sim N\left(\nu(\Delta V_{t-1,i}) + \beta(\Delta V_{t-1,i}) * (\Delta X_{t-1}^j - \mu(\Delta V_{t-1,i})), \right. \\
&\quad \left. [\theta(\Delta V_{t-1,i}) * \lambda^j(\Delta V_{t-1,i})]^{-1}\right) \\
\forall i &= 1, \dots, N; t = 2, \dots, 5
\end{aligned} \tag{2}$$

628 where the notation is analogous to that in equation (1) except that now N
629 unique distributions are estimated corresponding to each virtual observation.
630 Virtual observation $\Delta V_{t-1,i}$ is treated as a sample from an underlying normal
631 distribution; $\mu(\Delta V_{t-1,i})$ and $\nu(\Delta V_{t-1,i})$ are the underlying change in mean
632 temperature in the current ($t - 1$) and future (t) time periods respectively
633 given each virtual observation $\Delta V_{t-1,i}$; $\lambda^j(\Delta V_{t-1,i})$ is the reliability of model j
634 for virtual observation i in time t ; and $\beta(\Delta V_{t-1,i})$ and $\theta(\Delta V_{t-1,i})$ are estimated
635 uniquely for each virtual observation $\Delta V_{t-1,i}$.

636 This approach does have limitations. First, it assumes that GCMs are
637 independent of one another, when in fact some models borrow entire com-
638 ponents from other models [45]. Second, we assume that a GCM's ability
639 to reproduce ΔT or $\% \Delta P$ is a better indication of model performance than
640 another metric, such as model variability. Third, we assume that change
641 in time t depends on $t-1$ and not previous time periods. Additionally, we
642 assume climate models will not change in the future; repeating the analysis
643 in 40 years with a broader range of models reflecting the new state of the
644 science may produce larger shifts in CIs. However, this approach is the best
645 available to estimate learning in the future, which impacts planning deci-
646 sions today. It enables a more precise measure of uncertainty in comparison
647 to the democratic approach used by the IPCC; it has also been statistically
648 validated using a cross validation approach [25].

649 *Estimating transition probabilities*

Each estimate for $\nu(\Delta V_{t-1,i})$ (or ν_1 if $t=1$) is then used to estimate the probability of change in each temperature state T_t in the SDP temperature

state vector $S_T(t)$. (Note we treat $\nu(\Delta V_{t-1,i})$ as a probability mass function discretized at the same granularity as the virtual observations):

$$\begin{aligned} P(\Delta T_t \mid \Delta T_{t-1} = \Delta V_{t-1,i}) &= \nu(\Delta V_{t-1,i}) \\ P(\Delta T_t = a \mid \Delta T_{t-1} = \Delta V_{t-1,i}) &= P(\nu(\Delta V_{t-1,i}) = a) \\ \forall i = 1 \dots N; t = 1 \dots 1 \end{aligned} \quad (3)$$

We then define the joint distribution for the relative change probabilities using the chain rule and the Markov assumption, which is consistent with our assumption in the Bayesian model that the next time period is informed only by the previous one.

$$P(\Delta T_0, \Delta T_1, \dots, \Delta T_5) = P(\Delta T_0) * P(\Delta T_1 \mid \Delta T_0) * \dots * P(\Delta T_5 \mid \Delta T_4) \quad (4)$$

Combining (3) and (4), we relate the joint density of the temperature change probabilities to the Bayesian model from (1) and (2):

$$\begin{aligned} &P(\Delta T_0 = \Delta X_0, \Delta T_1 = \Delta V_{1,i}, \dots, \Delta T_5 = \Delta V_{5,m}) \\ &= P(\Delta T_0 = \Delta X_0) * P(\Delta T_1 = \Delta V_{1,i} \mid \Delta T_0 = \Delta X_0) * \dots \\ &\quad * P(\Delta T_5 = \Delta V_{5,m} \mid \Delta T_4 = \Delta V_{4,l}) \\ &= P(\mu_0 = \Delta X_0) * P(\nu_1 = \Delta V_{1,i}) * \dots * P(\nu(\Delta V_{4,l}) = \Delta V_{5,m}) \\ &\quad \forall i, j, k, l, m = 1, \dots, N \end{aligned} \quad (5)$$

650 Next, we develop a joint distribution for the absolute mean temperatures
651 in each time period, which correspond to the SDP temperature states $S_T(t)$.
652 To do this, we 1) assume $T_0 = X^* + \mu_0$, where X^* is a constant reflecting
653 the historical observed temperature in time t-1, and 2) recognize that the
654 absolute temperature in t is the sum of all the relative changes between 0
655 and t plus T_0 . The joint density of $S_T(t)$ is therefore:

$$\begin{aligned} &P(T_0 = a, T_1 = b, \dots, T_5 = f) \\ &= P(\mu_0 = a - X^*) * P(\nu_1 = b - a) * \\ &\quad P(\nu(\Delta V_{1,i}) = c - b) * \dots * P(\nu(\Delta V_{4,l}) = f - e) \\ &\forall i, j, k, l, m = 1, \dots, N \end{aligned} \quad (6)$$

where

$$\begin{aligned} a &= X^* + \Delta X_0, b = X^* + \Delta X_0 + \Delta V_{1,i}, \dots, \\ f &= X^* + \Delta X_0 + \Delta V_{1,i} + \Delta V_{2,j} + \Delta V_{3,k} + \Delta V_{4,l} + \Delta V_{5,m} \\ s.t. \quad a, b, c, d, e, f &\in S_T(t) \end{aligned}$$

656 The SDP temperature transition probabilities consist of adjacent time
657 period conditional probabilities i.e. $P(T_t = w|T_{t-1} = v)$. We use Monte
658 Carlo simulation to calculate them by sampling from the joint density in (6)
659 as follows:

- 660 1. Sample from (6) to generate M equally likely realizations of the joint
661 density. Each realization forms a set, Y_i , of the form:
662 $Y_i : \{T_0 = y_{0i}, T_1 = y_{1i}, T_2 = y_{2i}, T_3 = y_{3i}, T_4 = y_{4i}, T_5 = y_{5i}\} \forall i = 1, \dots, M$
- 663 2. Let P equal the number of sets Y_i out of the total of M for which $T_t = w$
664 and $T_{t-1} = v$
- 665 3. Let Q equal the number of sets Y_i out of the total of M for which
666 $T_{t-1} = v$

Then, the transition probabilities are:

$$P(T_t = w|T_{t-1} = v) = \frac{P(T_t = b, T_{t-1} = a)}{P(T_{t-1} = a)} = \frac{P}{Q} \quad \forall a, b \in S_T(t) \quad (7)$$

667 *Stochastic dynamic programming (SDP)*

668 Stochastic dynamic programming is an optimization approach and control
669 method that represents decision-making under uncertainty using multiple
670 stages or time periods. The result is optimal policies, representing the best
671 possible action as a function of the system state and time period. In our
672 non-stationary formulation, it can also be understood as a form of closed-
673 loop stochastic control, in which new information about the system feeds
674 back into updated estimates for system state transitions over time. This is
675 analogous to existing approaches in ecology, which have defined SDP transi-
676 tion probabilities with probability density functions that include the current
677 system state as an input [46, 47].

678 Optimal policies are derived by recursively solving the Bellman equation:

$$V(s, t) = \operatorname{argmin}_{a \in A} C(s(t), a(t), t) + \gamma \sum_{s \in S} p(s(t+1) | s(t), a(t)) * V(t+1, s(t+1)) \quad (8)$$

679 where V is the optimal policy, t is the time period, a is an action, s is
680 a state, γ is the discount rate, and $p(s(t+1) | s(t), a(t))$ are the transition
681 probabilities. The action a describes whether a static or flexible dam is cho-
682 sen, and whether infrastructure capacity is expanded in later time periods.

683 Costs C include the capital costs of infrastructure and damages if the infras-
684 tructure fails to meet reliability targets. The state space S includes mean
685 temperature S_T and mean precipitation S_P averaged over a 20-year period
686 and available infrastructure capacity S_Z . S_T , S_P , and S_Z are assumed in-
687 dependent. Therefore, the transition probabilities $p(s(t+1) | s(t), a(t))$ are
688 estimated as three independent transition vectors: the transition vector for
689 S_T is described in equations (4) and (5) and independent of $a(t)$, S_P is
690 analogous to S_T , and S_Z are deterministic based on the current capacity and
691 action to add capacity.

692 We formulate the Bellman equation as follows. The formulation is iden-
693 tical across planning scenarios A-C except where specified.

$$\begin{aligned}
S &= \{S_T(t), S_P(t), S_Z(t)\} \\
A &= e(S_Z, t) \\
C &= I(S_T, S_P, S_Z, e, t) + D * U(S_T, S_P, S_Z, e, t)
\end{aligned} \tag{9}$$

694 where

- 695 • $t \in \{1...5\}$ is a 20-year time period ranging from 2001-2020 for $t = 1$
696 to 2081-2100 for $t = 5$
- 697 • $S_T(t)$ is the mean temperature in °C in time period t , ranging from 25
698 to 33 at 0.05°C increments.
- 699 • $S_P(t)$ is the mean precipitation in mm/month in time period t , ranging
700 from 66 to 97 at 1 mm/month increments.
- 701 • $S_Z(t) \in \{1...4\}$ is the available infrastructure, in which the states corre-
702 spond to a small infrastructure alternative, large infrastructure alterna-
703 tive, flexible unexpanded alternative, and flexible expanded alternative,
704 respectively. The infrastructure alternatives are either a set of dams
705 (planning scenarios A and B) or a set of desalination plants (planning
706 scenario C).
- 707 • $e(S_Z, t) \in \{0...4\}$ is the choice of infrastructure in which 0 is no change,
708 1 is a small static alternative, 2 is a large static alternative, 3 is
709 a flexible alternative, and 4 is the expansion of the flexible alterna-
710 tive. The alternatives include a set of dams (planning scenarios A and
711 B) or a set of desalination plants (planning scenario C). The choices
712 are constrained by time period and available infrastructure such that

713 $e(S_Z, t = 1) \in \{1, 2, 3\} \forall S_Z$; $e\{S_Z, t\} \in \{0, 4\} \forall t = 2 \dots 5, Z = 3$; and
714 $e\{S_Z, t\} \in \{0\} \forall t = 2 \dots 5, Z = 1, 2, 4$

715 • I is the cost of the infrastructure including capital costs (capex) and
716 operating costs (opex). Desalination opex in planning scenario A is a
717 function of the water produced in each time period.

718 • D is unit cost of damages incurred for unmet water demand, set at 15 \$
719 /m³ in our base case based on estimates of water productivity in Kenya
720 from the World Bank [48].

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

726 *Stochastic weather generation*

727 Climate impacts on river runoff depend on changes in month-to-month
728 variability in precipitation and temperature in addition to changes in the
729 mean. We model these two changes separately. To develop monthly time-
730 series of T and P , we follow the k nearest neighbors (kNN) approach as
731 described in Rajagopalan et al., (1999) applied to GCM projections. This
732 non-parametric statistical approach allows us to impose the mean T and T
733 from the SDP while also capturing the standard deviation in monthly values
734 and month-to-month autocorrelation projected by the GCMs. This approach
735 was chosen for its simplicity and ease of implementation; future studies could
736 use other non-parametric approaches such as the local polynomial regression
737 method developed in [49]. For each 20-year time period, we employ the kNN
738 approach to generate 100 samples of 20-year long monthly time-series of T
739 and P . The resulting time series are then applied to the Rainfall-runoff model
740 presented below.

741 *Rainfall-runoff model*

742 Next, the synthetic T and P time series are input to a hydrological model
743 to assess the impacts on runoff. We use CLIRUN II, the latest in a fam-
744 ily of hydrological models developed to assess the impact of climate change

745 on runoff [50, 51, 52, 53]. CLIRUN II is a two-layer, conceptual, lumped-
746 watershed rainfall-runoff model. It averages soil parameters over the water-
747 shed and models runoff at one gauge station at the mouth of the basin. It can
748 be run on a monthly or daily time step. Using the kNN generated samples of
749 T and P, CLIRUN II generates a corresponding 100 samples of 20-year long
750 monthly timeseries of runoff.

751 CLIRUN II is calibrated using 14 years of monthly streamflow data. Only
752 one streamflow gauge, RGS 3MA03, is available in the Mwache basin [31].
753 However, it is directly upstream of the dam location, making it representative
754 for this study. The same monthly temperature and precipitation data from
755 CRU used in the Bayesian climate analysis is used to calibrate CLIRUN II
756 for consistency. This temperature and precipitation data is different than the
757 local data used in the previous World Bank study [20], leading to different
758 calibration results but similar performance (historical MAR: 113 MCM/y;
759 World Bank MAR: 133 MCM/y; our MAR: 103 MCM/y). Our analysis
760 using CLIRUN II and the reservoir sizing model confirms that the 80 MCM
761 dam meets the reliability targets in the current and expected future climate
762 but does not meet reliability targets if the climate gets substantially warmer
763 and drier. The 120 MCM dam meets reliability targets across all projected
764 future climates.

765 *Infrastructure costs and operations*

766 Capex and opex estimates for the small and large dams were developed
767 using the cost tool from the previous World Bank study [20]. For the flexible
768 dam, the cost per m^3 of additional capacity added is assumed to be 50%
769 greater than that of the original capacity. Capex and opex estimates for the
770 RO desalination plants were developed using the Cost Estimator tool from
771 DesalData [54].

772 The infrastructure operation model includes fixed dam operations (and
773 desalination operations when necessary) that seek to meet the specified yield
774 target while accounting for dead storage, net evaporation, and environmental
775 flows. Unmet demand is measured for each of the 100 streamflow time series,
776 and the average 20-year unmet demand is used to characterize U in the
777 SDP formulation in equation 9. We acknowledge that assuming reservoir
778 operations that are fixed in time is a limitation given that adaptive reservoir
779 operations would likely reduce the need for additional capacity; future work
780 could optimize the reservoir operations to each climate state.

781 **Supplementary Information**

SI Table 1: Climate model ensembles used

Modeling Center	Institute ID	Model Name (ens. member)
Commonwealth Scientific and Industrial Research Organization 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)