

Dam reoperation to mitigate changing climate extremes in the Omo River valley

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Abstract

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Dam reoperation to mitigate changing climate extremes in the Omo River valley

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ABSTRACT

Climate change is projected to increase the intensity and frequency of extremes in river basins around the world. Water infrastructure such as reservoirs are often used to buffer against these extremes, enabling more reliable water supply for human uses like irrigation. Yet this can have negative impacts on the system's ecological flows. In designing water infrastructure for human adaptation to climate change, it is important to consider whether the infrastructure is mitigating or exacerbating climate change impacts on ecological systems. Prior work has found that dams mitigate long-duration extremes but exacerbate short-duration extremes. In this study, we investigate whether reservoir operations can be designed to also yield beneficial climate adaptation outcomes for short-duration high and low flow extremes while still improving average socioeconomic and ecological objectives compared to uncontrolled conditions. We explore this research question

24 in the Omo River Basin in Ethiopia, where controversy surrounding socio-ecological impacts of
25 recent and ongoing dam construction make this a pressing issue to understand. Using multi-
26 objective optimization of reservoir control rules, we are able to find several policies that can in
27 fact mitigate the impact of climate change on annual maxima and annual 7-day minima. While
28 we do see tradeoffs across reservoir operating policies that best preserve the distribution of these
29 two statistics, we also find compromise policies that mitigate both of these extremes compared to
30 uncontrolled conditions. This shows promise for the role dams can play in climate adaptation to
31 short-duration flow extremes, if their operations are designed with multiple objectives in mind.

32 INTRODUCTION

33 Climate change is expected to intensify the hydrologic cycle, and such behavior is already being
34 observed in river basins around the world (Ficklin et al. 2022; Markonis et al. 2019; Huntington
35 2006). Changes in precipitation patterns, soil moisture content and runoff, and increasing frequency
36 and intensity of extreme rainfall events are causing more extreme floods and droughts (Boulangé
37 et al. 2021; Bates et al. 2008). Water resources managers have often relied on reservoirs to mitigate
38 these conflicting risks while still meeting other economic, agricultural, social, and ecological river
39 basin demands (Hall et al. 2014). Consequently, climate adaptation research has largely focused on
40 mitigating impacts by increasing infrastructure development, such as building new dams, restoring
41 or increasing the size of old dams, or transferring water between catchments to balance supplies
42 during drought (Watts et al. 2011; Poff et al. 2016; Zeff et al. 2016).

43 However, dam planning, construction, and maintenance are all expensive and time-intensive,
44 often costing billions of dollars over many years to complete. For this reason, the economic benefits
45 associated with dams have historically been the primary drivers in decisions about how and when
46 water is released from reservoirs to make up for their large capital costs (Hurford and Harou 2014;
47 Ho et al. 2017). Yet maximizing the economic benefits of water releases from reservoirs disrupts
48 natural flow regimes, which can fragment free-flowing rivers (Graf 2001), severely alter or destroy
49 aquatic ecosystems (Liermann et al. 2012; Poff and Hart 2002; Goodland 2010), restrict access to
50 water resources, cause transboundary conflicts (Zarfl et al. 2015), and hamper water quality (Gyasi

51 [et al. 2018](#)). Most concerning, dams may displace communities, making them both socially and
52 politically controversial ([Ehsani et al. 2017](#); [IUCN Water 2019](#)). To date, dam construction has
53 displaced 40-80 million people worldwide, disproportionately affecting indigenous populations
54 ([Goodland 2010](#); [Babbitt 2002](#)).

55 Given these concerns, recent research has focused on integrating social and environmental
56 objectives into siting, sizing and operating dams ([Arnold et al. 2023](#); [Watts et al. 2011](#); [Olden et al.](#)
57 [2014](#); [Zarfl et al. 2015](#); [Sabo et al. 2017](#); [Schmitt et al. 2018](#); [Wild et al. 2019](#); [Flecker et al. 2022](#);
58 [Hatchard et al. 2023](#)). However, it is not clear that these designs will still be sufficient under climate
59 change. Altered precipitation patterns could reduce river flows, decreasing the projected economic
60 benefits from hydropower production, stranding over-designed assets at the expense of displaced
61 communities and the ecology ([Cole et al. 2014](#)). On the flip side, under-designed infrastructure
62 could lead to increased risks of floods or droughts ([Lumbroso et al. 2015](#)). Climate change impacts
63 on flow patterns as well as increased instances of floods and droughts will be felt in absence of
64 infrastructure development as well, though. The interaction between dam operations and climate
65 on downstream flow alteration is complex. Some studies have found that dams mitigate the effects
66 of climate change ([Yun et al. 2020](#); [van Oorschot et al. 2018](#); [Giuliani et al. 2016a](#); [Mueller 2007](#))
67 while others have found that climate change impacts exceed the impacts of dams and other human
68 interventions ([Ficklin et al. 2018](#)), or that dams exacerbate climate change impacts ([Mittal et al.](#)
69 [2016](#)). [Chalise et al. \(2021\)](#) found that the combined influence of dams and climate trends can either
70 enhance or diminish overall alteration at a local level, deviating what would be predicted based on
71 their isolated effects: dams may intensify, ameliorate, or produce dual effects on flow alterations
72 driven by hydroclimate depending on the observed climate trends, dam size, and dam purpose(s).
73 Of note, they found that dams generally mitigate the impacts of climate change on long-duration
74 extremes (30-90 day high or low flows) but exacerbate their impacts on short-duration extremes
75 (1-7 day high or low flows). This begs the question: “Can alternative operations be discovered that
76 also mitigate the impacts of climate change on these short-duration extremes, while still improving
77 expected socioeconomic and ecological performance compared to uncontrolled conditions?”

78 In this study, we investigate whether closed loop operating policies can do just that: reduce
79 socio-ecological tradeoffs while also mitigating the impacts of climate change on short-duration
80 high and low flow extremes. We explore this question in the Omo River Basin of Ethiopia (Figure
81 1), a basin grappling with these economic development and climate change adaptation challenges
82 (Zaniolo et al. 2021b; Jordan et al. 2022). Over the past two decades, three hydro-electric facilities
83 have been constructed along the Omo River (Gilgel Gibe I, II, and III), with a fourth power plant
84 under construction (Koysa). At the time of its construction, Gibe III increased Ethiopia's installed
85 hydroelectric capacity by 80%, and, upon completion, the Koysa dam will be the second largest
86 dam in the country, after the Grand Ethiopia Renaissance Dam. With a combined capacity of
87 4,634 MW and 21,202 Mm^3 of reservoir storage, these dams can help promote economic growth
88 in the region by offering stable hydropower generation and a reliable water supply for irrigation
89 of new large-scale private sugarcane and cotton plantations (Woodroffe 1996; IEA 2016; Asress
90 et al. 2013; Zaniolo et al. 2021a; Sundin 2017; Avery 2012; Davidson 2015; Hodbod et al. 2019;
91 Oakland Institute 2011; Human Rights Watch 2017). However, the dams have also altered the
92 historical flow pattern influenced by monsoonal rains, posing risks to the indigenous communities
93 practicing recession agriculture, and ecosystems in the Lower Omo Basin and Lake Turkana at its
94 mouth (Hathaway 2009; Abbink 2012; Fratkin 2014; Carr 2017; Johnston 2009).

95 In prior work, we designed reservoir operating policies in the Omo River Basin to balance
96 competing economic and socio-ecological objectives, and then assessed how robust performance
97 on these objectives was to possible climate futures (Giuliani et al. 2022; Jordan et al. 2022).
98 However, all of these objectives focused on mean performance, when the greatest concerns about
99 climate change are its impacts on extremes. In Jordan et al. (2022), we constrained operations not to
100 exceed historical maximum flows and to meet minimum environmental flow thresholds downstream
101 of the dams when simulated over the historical record. Yet changing climatic stressors may force
102 these conditions to be violated, which could create a new set of challenges in the basin. Here we
103 perform a climate risk assessment to determine whether our optimized operating policies can also
104 mitigate the impacts of climate change on short-duration high and low flow statistics. While the

105 findings of this study are specific to the Omo River Basin, the work illustrates a framework that can
106 be applied to other locations to both design reservoir operations to manage conflicting objectives,
107 and to assess the applied research question of whether reservoirs can mitigate the impacts of climate
108 change on short-duration high and low flow extremes.

109 **METHODS**

110 To answer this study's research question on whether water infrastructure can mitigate climate
111 change impacts on short-duration high and low flow extremes, we utilize the Multi-Objective
112 Robust Decision Making (MORDM) framework (Kasprzyk et al. 2013). MORDM is one of several
113 robustness analysis methods used to find water management strategies for balancing conflicting
114 objectives under uncertainty. In this study, we use MORDM in a new way to investigate whether
115 reservoir operations mitigate or exacerbate climate change impacts, determined by whether they are
116 more or less robust the projected uncontrolled conditions in reproducing distributions of high and
117 low flows extremes experienced under historical uncontrolled conditions. Following the robustness
118 taxonomy of Herman et al. (2015), our application of MORDM first defines alternative reservoir
119 operating policies to evaluate using multi-objective optimization. Second, the performance of
120 these policies is evaluated under different states of the world defined by climate projections from
121 the Coupled Model Intercomparison Project 5 (CMIP5). While there may be other uncertainties
122 that could influence performance beyond climate change, such as population growth and land use
123 change, we focus our analysis on the specific research question of how climate change impacts
124 the system with and without reservoir infrastructure. Third and finally, we answer our research
125 question by quantifying the robustness of the operating policies using a satisficing metric specifying
126 the percent of the climate projections in which high and low flow extremes are mitigated compared
127 to a no-infrastructure scenario. These three steps of the MORDM process are described below.

128 **Multi-Objective Optimization**

129 This study builds off prior work by Jordan et al. (2022) in which a new reservoir optimization
130 module was incorporated into the Soil and Water Assessment Tool (SWAT), enabling the joint
131 exploration of changing reservoir operations and climate conditions on socio-ecological perfor-

132 mance metrics. In the new reservoir optimization module, reservoir operating rules are described
 133 by Gaussian radial basis functions (RBFs) that define how much water to release from system
 134 reservoirs as a function of different state variables, such as the reservoir storage and day of the year.
 135 Mathematically, this can be described by equation 1:

$$136 \quad u_t^k = a_k + \sum_{i=1}^N w_{i,k} \exp \left(\sum_{j=i}^B \frac{((v_t)_j - c_{i,j})^2}{b_{i,j}^2} \right) \quad (1)$$

137 where u_t^k is the normalized release from the k -th reservoir at time t , $(v_t)_j$ is the j -th normalized
 138 input variable at time t , B is the number of input variables, N is the number of RBFs, and a_k ,
 139 $w_{i,k}$, $c_{i,j}$ and $b_{i,j}$ are constant parameters to be optimized. In this study, $B = 5$ inputs were used:
 140 the volume of the three storage dams at time t (Gibe II does not have storage), and two variables
 141 capturing seasonality: $\sin(2\pi t/365)$ and $\cos(2\pi t/365)$. The policies were defined by $N = 9$ RBFs,
 142 and $K = 3$ for the releases from the three storage dams. This yielded a total of $K + N(2B + K) = 120$
 143 decision variables.

144 **Jordan et al. (2022)** used a simulation-optimization approach called Evolutionary Multi-
 145 Objective Direct Policy Search (EMODPS; **Giuliani et al. (2016b)**) to optimize these 120 pa-
 146 rameters. In the simulation phase, the true releases from the reservoirs, r_t^k , are determined by
 147 back-transforming the normalized releases and then subjecting them to physical and minimum en-
 148 vironmental flow constraints. At the end of the simulation, multiple performance metrics are com-
 149 puted. A multimaster parallelization of the Borg multi-objective evolutionary algorithm (MOEA;
 150 **Hadka and Reed (2013, Hadka and Reed (2015))**) was used to optimize the RBF parameters to
 151 improve the performance of these objective functions. This process yields a ‘‘Pareto set’’ of alterna-
 152 tive reservoir operating policies, p_θ^* , in which no policy outperforms another on all objectives, but
 153 rather requires trading off performance across them. The objectives were to 1) maximize average
 154 annual hydropower production (GWh/year), 2) minimize average squared deviations from mean
 155 daily flow targets for environmental flows (cms²/day), 3) minimize average daily squared deviations
 156 below flow targets for flood-recession agriculture during the growing season (cms²/day), and lastly

157 maximize average annual production of 4) sugarcane and 5) cotton in the Omo River Basin (metric
 158 tons/year). The optimization problem is described by equations 2-5:

$$159 \quad p_{\theta}^* = \operatorname{argmin}_{p_{\theta}}(\bar{J}) \quad (2)$$

$$160 \quad \theta = [a_k, w_{i,k}, c_{i,j}, b_{i,j}] \quad (3)$$

$$161 \quad \bar{J} = | -J^{hyd}, J^{env}, J^{rec}, -J^{sug}, -J^{cot} | \quad (4)$$

162 subject to:

$$163 \quad \max(q_{max}^{LO} - q_{hmax}^{LO}, 0) = 0 \quad (5)$$

164 where J^{hyd} , J^{env} , J^{rec} , J^{sug} , and J^{cot} are the system objectives defined by equations 8-12 in
 165 Appendix I. q_{max}^{LO} is the maximum simulated flow in the Lower Omo, which is constrained not to
 166 exceed q_{hmax}^{LO} , which equals $3,290 \text{ m}^3/\text{s}$, the historical maximum flow simulated by SWAT over
 167 the same period (1989-2018) in absence of reservoirs. This constraint was included to ensure that
 168 reservoir releases would not inundate the Lower Omo Valley. All objectives and constraints were
 169 developed through a participatory process with stakeholders in the basin through “Negotiation
 170 Simulation Labs” held as part of the DAFNE project (Giuliani et al. 2022).

171 **Jordan et al. (2022)** showed that the Pareto-optimal reservoir operations defined by these RBFs
 172 were better able to compromise across system objectives than operations designed using prior
 173 SWAT operating rule forms. Furthermore, many of these policies enabled better performance
 174 across all objectives than if there were no reservoirs, both under historical and projected future
 175 climate conditions.

176 *Limitations of Optimization Objectives*

177 While the operation objectives defined in the preceding section serve as mathematical rep-
 178 resentations of conflicting stakeholder needs in our optimization framework, it is important to
 179 acknowledge the potential distinctions between these mathematical framings and the nuanced real-

180 world operating objectives of hydropower facilities. For example, the hydropower objective seeks
181 to maximize average annual hydropower output, but does not respond to changes in seasonal or
182 inter-annual demand. However, in absence of information on electricity market prices, maximizing
183 hydropower production is a close proxy, and in alignment with Ethiopia’s goal of becoming an
184 energy exporter. With respect to environmental flows and recession agriculture, these objectives
185 are both designed to re-create natural flow patterns in the Omo River basin, enabling the design of
186 operating policies that mimic the cyclo-stationary hydrograph. However, these objectives do not
187 capture year-to-year variability that can benefit many ecosystems (Whipple and Viers 2019). While
188 there could be alternative mathematical formulations that better capture stakeholders’ objectives,
189 our process of identifying alternative operations and assessing their ability to mitigate climate
190 change impacts on different operating objectives can easily be applied to alternative mathematical
191 formulations of these operating goals.

192 **Definition of States of the World**

193 Whether reservoir operations mitigate or exacerbate the impacts of climate change is likely to
194 depend highly on the distribution of future stochastic inflows. Operations may mitigate impacts
195 in some potential futures and exacerbate them in others. We seek to identify if operating policies
196 can more closely reproduce historical uncontrolled conditions across more possible distributions of
197 future stochastic inflows than projected uncontrolled conditions. To identify “possible distributions
198 of future stochastic inflows” we define different possible future “states of the world” from down-
199 scaled CMIP5 climate projections. The goal is to see if the operating policies identified by Jordan
200 et al. (2022) not only reduce the mean socio-ecological tradeoffs of reservoir development, but also
201 provide adaptation strategies that mitigate impacts of climate change on extreme short-duration
202 flood and drought conditions across more possible futures. We use the same 48 downscaled climate
203 projections described in Jordan et al. (2022). The reader is directed to that study for more details on
204 the downscaling method. The 48 downscaled projections consist of 17 general circulation models
205 (GCMs) run under different representative concentration pathways (RCPs) ranging from 2.6-8.5.
206 The models and scenarios are listed in Appendix II Table 1.

207 Of course, alternative scenarios could be used for robustness analysis, such as CMIP6 projections
208 rather than CMIP5, and the true future may lie beyond the uncertainty of either of these projections.
209 Prior studies have shown that alternative ensembles may result in different policy rankings on
210 robustness metrics (Reis and Shortridge 2020; McPhail et al. 2020; Quinn et al. 2020; Bonham
211 et al. 2024). However, ranking inconsistencies occur within a neighborhood of similarly ranked
212 policies; globally rankings are quite consistent. Consequently, if *several* policies are more robust
213 than historical uncontrolled conditions, this should hold for at least some of those policies under
214 alternative ensembles, and we can be confident that optimized operations can mitigate impacts of
215 climate change.

216 **Robustness Calculation**

217 *Definition of Wet and Dry Extremes and Operational Robustness*

218 To discern whether optimized reservoir operating policies mitigate or exacerbate short-duration
219 wet and dry hydrological extremes, we first define metrics quantifying these conditions. To capture
220 extreme wet and dry conditions, we select two of the 33 indicators of hydrological alteration defined
221 by Gao et al. (2009), with a focus on short-duration extreme flow statistics: the annual maximum
222 daily flow and the minimum 7-day average flow. We denote the time series of annual maximum
223 daily flows in the Omo River delta the annual maxima series (AMS). Annual maxima series are used
224 in flood frequency analysis to aid flood management, reservoir planning, and irrigation scheduling
225 (Tiwari et al. 2017).

226 We denote the time series of annual minimum seven-day flow series as 7QS. This flow indicator
227 captures both persistence (seven-day average) and severity (minimum). Average flows over shorter
228 or longer windows can alternatively be used to capture more intense or persistent ecological drought
229 impacts. Our environmental flows objective should capture impacts on long-duration low flows,
230 and prior work by Chalise et al. (2021) found dams tend to mitigate climate change impacts on these
231 statistics. We seek to discover if operations can mitigate shorter-duration extremes. Our minimum
232 environmental flow constraint on the reservoir releases should reduce the intensity one-day low
233 flows, but we have no explicit mechanism in our optimization to control seven-day low flows. As

234 such, we choose this duration for our analysis as a robustness check on our optimized reservoir
235 operating policies. Seven-day low flows are also used frequently to define environmental droughts
236 such as the most commonly used low flow index in the United States: the seven-day, ten-year low
237 flow, or 7Q10, defined as the annual minimum seven-day low flow that occurs, on average, once
238 every ten years (Riggs 1980).

239 Gao et al. (2009) use flow indicators like annual seven-day minima to calculate indices of
240 hydrological alteration, quantified as the integrated difference between the distribution of these
241 variables before and after infrastructure development. Following Kroll et al. (2015), we instead
242 perform hypotheses tests to see whether the altered distribution is statistically different from the
243 natural distribution. To do this, we calculate AMS and 7QS time series in the Omo River delta
244 from SWAT simulations under a historical uncontrolled scenario (HUC) from 1989-2018, as well
245 as projected uncontrolled scenarios (PUC) from 48 downscaled climate scenarios at mid-century
246 (2040-2069). This allows us to assess how ecological low flow and flood risks might change in the
247 future without reservoir infrastructure, i.e. in absence of adaptation. We repeat this process using
248 each of the optimized reservoir release policies from Jordan et al. (2022) to see if these operating
249 rules exacerbate or mitigate these changing vulnerabilities. We then compute the “robustness”
250 of each operating policy and PUC using a satisficing metric quantified as the percent of climate
251 projections in which some minimum performance threshold is met (Starr 1963; Schneller and
252 Sphicas 1983). Here we define three minimum performance thresholds: no statistically significant
253 difference in the distribution of 1) 7QS, 2) AMS, or 3) Both 7QS and AMS compared to HUC.
254 Operating policies with a higher satisficing metric than PUC tend to mitigate the impacts of climate
255 change on extremes, whereas operating policies with a lower satisficing metric tend to exacerbate
256 the effects of climate change. We define the policy that performs best on each of these metrics as
257 the Low Flows, High Flows, and Compromise policies, respectively.

258 *Statistical Analyses*

259 Following Kroll et al. (2015), we compare the distributions of historical and future AMS and
260 7QS time series using the two-sample Kolmogorov-Smirnov (K-S) test to help identify which

261 policies are mitigating or exacerbating the effects of climate change on extreme high and low
 262 flows. For each of the Pareto-optimal operating policies discovered from the optimization and the
 263 projected uncontrolled scenario, we use the K-S test to see if the distributions of the AMS and
 264 7QS in each of the climate projections are statistically different from the historical uncontrolled
 265 scenario (1989-2018) at mid-century (2040-2069). Based on the K-S test results, we then calculate
 266 the percent of projections in which each policy's distributions of high and low flows do *not* have a
 267 statistically significant difference from the historical uncontrolled scenario ($p > 0.05$). Reservoir
 268 operating policies that are not statistically different from HUC in a greater percentage of projections
 269 than PUC mitigate the impacts of climate change on low flows.

270 In each projection, we also test whether or not there is a monotonic trend in the 7QS and
 271 AMS time series for each policy and the uncontrolled scenario. Operating policies that reduce
 272 the number of projections in which these time series exhibit a monotonic trend compared to the
 273 projected uncontrolled scenario provide favorable climate adaptation. We use the non-parametric
 274 Mann-Kendall trend test for this analysis (Mann 1945; Kendall 1948). The Mann-Kendall trend
 275 test is used to test if there is a monotonic trend by comparing each value in a time series with all
 276 future values and tracking the number of increases, decreases, and ties across all timesteps. The
 277 test statistic, Z , is then computed from S , the difference between the number of positive changes
 278 and the number of negative changes across all timesteps, and V , its variance:

$$279 \quad Z = \begin{cases} \frac{S-1}{\sqrt{v}} & \text{if } S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{v}} & \text{if } S < 0 \end{cases} \quad (6)$$

$$280 \quad V = \frac{n(n-1)(2n+5) - \sum_{i=1}^n t_i(i-1)(2i+5)}{18} \quad (7)$$

281 where n is the number of time steps, t_i is the number of ties and i is the extent of the tie. Z is
 282 normally-distributed, so if $Z < 1.96$ there is a statistically significant decreasing trend, while if

283 $Z > 1.96$, there is a statistically significant increasing trend ($\alpha = 0.05$).

284 **RESULTS AND DISCUSSION**

285 The results of our analysis are organized as follows. First, we illustrate the ability of the reservoir
286 operating policies to balance socio-ecological tradeoffs over the historical record compared to
287 uncontrolled conditions. Next, we assess their ability to mitigate changing high and low flow
288 extremes with respect to preserving their distribution and reducing their trends. Finally, we
289 investigate their ability to reproduce historical seasonality into the future, and to better balance
290 socio-ecological objectives than without infrastructure.

291 **Ability of reservoir operations to balance socio-ecological tradeoffs over the historical record**

292 First we investigate how well alternative reservoir operations can balance conflicting socio-
293 ecological objectives in the Omo River Basin compared to historical uncontrolled conditions
294 (HUC). The historical performance of optimized reservoir operating policies is plotted on a parallel
295 axis plot in Figure 2, in which each colored line represents a different operating policy that crosses
296 each axis at its performance on that axis's objective, where the favorable direction on each axis is
297 down. The color of each line represents that policy's performance on the environment objective,
298 with green policies performing the best and red policies performing the worst. Recall that the
299 environment objective is to minimize squared deviations from a cyclostationary mean daily flow
300 sequence, so policies that consistently follow that pattern each year are favored.

301 For reference, the performance of HUC on all objectives is shown by a black dashed line.
302 From Figure 2a, we see that many of the policies in red do well on sugar and cotton production at
303 the expense of performing worse than HUC on meeting the environment objective, illustrating a
304 tradeoff in performance. However, there are also many policies that are able to outperform HUC
305 on all objectives. Figure 2b has made all these policies opaque, while those that are outperformed
306 by HUC on at least one objective are transparent. Fortunately, about half of the policies remain
307 opaque, meaning they are able to outperform HUC on all objectives over historical conditions.

308 While it is expected that reservoir operations would enable improved hydropower, sugar cane,
309 and cotton production, it is counter-intuitive that they could improve environmental flows. We find

310 this because the environment objective rewards replication of cyclostationary conditions without
311 year-to-year variability. While the objective is designed to ensure operational strategies recreate
312 naturally-occurring seasonality of high and low flows in the Omo River basin, we recognize that
313 some interannual variability is beneficial to many ecosystems (Whipple and Viers 2019). When
314 certain policies perform “better” than the uncontrolled scenario on this objective, it means that
315 these policies are more commonly replicating the cyclostationary mean flows than was possible
316 without reservoir operations, and not necessarily that the Lower Omo and Lake Turkana are in a
317 better ecological condition than they were prior to dam construction.

318 **Ability of reservoir operations to mitigate changing climate extremes**

319 While Figure 2b shows that several reservoir operating policies can outperform HUC on all
320 objectives over the historical record, this may change in the future, as climate change is expected
321 to increase extreme wet and dry flow conditions. Here we investigate whether reservoir operations
322 can mitigate those changes compared to projected uncontrolled conditions.

323 *Identification of robust operating policies*

324 Figure 3a-c shows the satisficing metric of all operating policies at mid-century on (a) low flows,
325 (b) high flows, and (c) both low and high flows by an orange line. Policies are sorted within each
326 panel from those with the highest satisficing metric to the lowest. A black line also indicates the
327 satisficing metric under PUC, while the best policy on each metric is indicated by orange, blue, and
328 white vertical lines for low flows, high flows, and both low and high flows, respectively. We refer
329 to these policies as the “Best Low Flow Policy”, “Best High Flow Policy”, and “Best Compromise
330 Policy”, respectively, throughout the remainder of the paper. For context, the performance of these
331 three policies on the optimization objectives over the historical record is shown in Figure 3d. Over
332 the historical record, the Best Low Flow Policy outperforms HUC on all objectives, while the Best
333 High Flow Policy does better on all but environmental flows, and the Best Compromise Policy does
334 better on all but cotton production.

335 In Figure 3a, we can see that there are a few policies that perform better in preserving historical
336 uncontrolled low flows than PUC, suggesting operating policies *can* be designed to mitigate these

337 short-duration low flow extremes. Yet most policies dampen short-duration low flows, as found in
338 [Chalise et al. \(2021\)](#). However, Figure 3b shows that many policies preserve pre-dam high flow
339 extremes better than the uncontrolled scenario, contrary to their findings. We will explore if this
340 might be from reservoirs dampening increasingly high extreme flows in wet projections, reservoirs
341 supplementing decreased high flows in particularly dry projections, or a combination of the two.
342 Finally, the Best Compromise Policy preserves pre-dam high *and* low flows in only about 37% of
343 climate projections considered, highlighting the trade-off in mitigating these two different types
344 of water resources extremes (Figure 3c). However, while this is low, it is even lower for PUC. In
345 fact, several policies maintain pre-dam extreme distributions of both high and low flows in more
346 projections than PUC. Note, that does not mean these policies preserve extreme high flows in more
347 projections than PUC *and* they preserve extreme low flows in more projections than PUC; rather
348 it means that for these policies, there are more projections in which *both* of these distributions are
349 preserved simultaneously than for PUC. The fact that so many policies outperform PUC on both
350 1) the high flows and 2) high and low flows satisficing measures suggests that even if a broader
351 ensemble of climate uncertainty were used, or alternative projections such as CMIP6, there would
352 be some optimized policies that can outperform HUC on these metrics.

353 Comparing the best policies on these different robustness metrics, we see clear trade-offs; the
354 Best High Flow Policy is the worst of the three policies in preserving historical low flows, and the
355 Best Low Flow Policy is the worst of the three policies in preserving historical high flows. The
356 Best Compromise Policy, which best preserves both high and low flows, strikes a better balance in
357 managing these extremes; it performs just about as well as the projected uncontrolled scenario in
358 preserving low flow extremes (Figure 3a), while outperforming the projected uncontrolled scenario
359 in preserving high flows (Figure 3b) and both high and low flow extremes together (Figure 3c).

360 Interestingly, while these policies have evident tradeoffs between high and low flow robustness,
361 both the low flow and compromise policy perform similarly (and quite well) on the environmental
362 flows objective historically (Figure 3a). This highlights the importance of considering multiple
363 ecological performance objectives, as policies that perform similarly on reproducing mean flows and

364 seasonality targeted by the environmental flows objective (see equation 9) may not be reproducing
365 extremes in the same way.

366 Throughout the rest of the paper, we will explore the Best High Flow Policy, the Best Low Flow
367 Policy, and the Best Compromise Policy in more detail. However, there are a number of policies
368 that outperform the projected uncontrolled scenario across climate projections at mitigating low
369 flows, high flows, or both while tracing different trade-offs in the objective space. The policies
370 explored in the paper therefore represent just one pathway for mitigating extreme flows, achieved
371 through a specific set of trade-offs between the optimization objectives considered in this study.

372 *Evaluation of extremes distributions for select policies*

373 We visualize the distributions of short-duration high and low flows from the four robust operating
374 policies and the projected uncontrolled conditions using a plot of their empirical cumulative
375 distribution functions (ECDFs; Figure 4). Each line represents a separate climate projection,
376 colored by the average flow in the Omo Delta in that projection's uncontrolled scenario as a
377 proxy for how wet or dry that climate projection is. The distribution under historical uncontrolled
378 conditions is shown in black. Projections in which the 7QS and AMS distributions do not statistically
379 significantly differ from the historical uncontrolled scenario are bold and opaque, while those that
380 are statistically significantly different are thin and transparent. Which projections have no statistical
381 difference in the ECDF from HUC is also shown in the binary color bar at the right of each figure.
382 In each color bar, the climate projections have been sorted from wet at the top to dry at the bottom
383 and colored black if the distribution is not statistically different than HUC, and white otherwise.

384 Projections produce a wider spread in extreme short-duration low and high flows compared to
385 the historical uncontrolled scenario. This is unsurprising, as climate change is projected to cause
386 both more severe droughts and more intense flooding (Trenberth 2011; Boulange et al. 2021; Bates
387 et al. 2008). The projected uncontrolled scenario preserves historical seven-day low-flows fairly
388 well, except for in the driest future conditions (Figure 4a). However, uncontrolled scenarios only
389 preserve the distribution of annual maxima in very dry projections, which suggests that there is
390 an increased flood risk in most projections (Figure 4b). The best policy for preserving low flow

391 distributions is able to preserve the distribution of low flows in many projections that are both
392 wet and dry (Figure 4c), but only preserves the distribution of high flows in a few moderately wet
393 climate projections (Figure 4d). While this suggests that this policy may dampen high flows in dry
394 projections, its performance on the recession agriculture objective almost always outperforms the
395 projected uncontrolled scenario across projections (see Figure 7). However, it fails to mitigate the
396 most extreme flood events, where flows reach nearly 10,000 cms, which would be a devastating
397 flood for indigenous populations in the Lower Omo Valley.

398 The best policy for preserving high flow distributions mirrors the historical uncontrolled high
399 flow distribution in most projections (Figure 4f). However, this policy completely alters the
400 distribution of low flows across all climate projections, severely reducing seven-day low flows
401 in all but a few extremely wet projections (Figure 4e). This would have a devastating effect on
402 indigenous people and ecological health in the Lower Omo Valley. Future work should explore if
403 reduced irrigation abstractions could improve socio-ecological outcomes from this policy without
404 sacrificing a large portion of annual yields.

405 While very wet conditions are needed for the Best Low Flow Policy to preserve HUC's high
406 flow distributions, and for the Best High Flow Policy to preserve HUC's low flow distributions,
407 the Best Compromise Policy is able to preserve the distribution of both high and low flows fairly
408 well across almost all projections (Figures 4g and 4h). This highlights the value of multi-objective
409 optimization in not only identifying solutions that can compromise across conflicting objectives,
410 but also adapt to a range of climate conditions, continuing to balance competing concerns.

411 *Trend identification in extremes for select policies*

412 We next identify trends in short-duration high and low flows from historical observations to
413 the end of mid-century for the projected uncontrolled scenario and the three robust policies using
414 the Mann-Kendall trend test. We summarize the results in Figure 5, where we show the percent of
415 projections with no trend from historical in gray, with an increasing trend in blue, and a decreasing
416 trend in orange.

417 In absence of water infrastructure development (the projected uncontrolled scenario), the seven-

418 day low flows show no trend in 50% of the climate projections, an increasing trend in 25% of
419 projections, and a decreasing trend in 25% of projections. The Best Low Flow Policy and the Best
420 Compromise Policy both increase the share of projections in which there is no trend in low flows
421 while decreasing the share of projections in which low flow extremes increase. This indicates the
422 reservoirs are able to replenish otherwise decreasing flows in several climate projections, enabling
423 favorable adaptation. The best policy for preserving high flow distributions, however, drastically
424 increases the share of projections with a decreasing trend in low flows, indicating unfavorable
425 adaptation.

426 With respect to high flows, the projected uncontrolled scenario most commonly shows a statis-
427 tically significant increasing trend of the annual maxima series from the historical time period to
428 mid-century, which highlights an increased flood risk to downstream communities under climate
429 change in absence of infrastructure development (Figure 5b). This could have negative implications
430 for recession agriculture as well. The robust policies considered here clearly help mitigate that risk,
431 increasing the share of projections under which there is no trend or a decreasing trend in the annual
432 maxima series. Once again, the compromise policy appears to be a favorable solution, yielding no
433 meaningful change in the number of projections with low flow trends while decreasing the number
434 of projections with increasing high flow trends.

435 **Ability of reservoir operations to reproduce historical seasonality and socio-ecological objec-** 436 **tives**

437 Figure 3 showed that reservoir operations can mitigate changes in extreme short-duration high
438 and low flows that would otherwise be projected under uncontrolled conditions. Yet it is important
439 to reproduce mean performance as well, particularly for standard operating objectives. Here we
440 investigate how typical flow conditions and operating objectives are projected to change when using
441 different operating rules compared to uncontrolled conditions.

442 For each robust policy, we use simulated flows in the Omo River delta across projections to
443 estimate the relative frequency of observing different flow magnitudes downstream of the dams
444 over the course of the year. Figure 6 shows the percent of simulated years in which the flow was

445 at different magnitudes each calendar day, with high frequencies shaded red, moderate frequencies
446 yellow, and low frequencies blue. The solid black lines show the historical daily high and low flow
447 magnitudes for each day of the year and the dashed black line shows the historical daily median.
448 While certain projections produced flows higher than 4,000 cms, we bound the plot to this range for
449 visualization purposes because flow events greater than 4,000 cms are so rare that they are difficult
450 to see on the plot and we already explored how the distribution of extremes changed above.

451 Across policies, the shape of the frequency distributions is similar over time, with flows of the
452 highest frequency in red rising in July for the rainy season and decreasing again in late October,
453 generally mirroring the historical median. However, there are some key differences. The Low Flow
454 and Compromise policies most frequently keep flows at or slightly above the historical median
455 during the dry period from January to March (Figures 6b and 6c). They are also able to reduce the
456 amount by which the lowest flows during the wet season fall below the historical low during this
457 period compared to PUC. Similarly, they are able to reduce the frequency of exceedances of the
458 historical maxima throughout the year compared to PUC.

459 The best policy for preserving high flows most effectively reduces the frequency of flows
460 above the historical maximum compared to PUC; however, it does this by completely altering the
461 seasonality of flows in the Omo River, drawing out the wet season flows so that the peak occurs
462 later than historically (Figure 6d). In prior work, we found such behavior to be favorable for cotton
463 production (Jordan et al. 2022), which this policy heavily favors. However, while the changed
464 seasonality for cotton production has the unintended benefit of reducing high flows, it comes at
465 the expense of preserving mean annual environmental flows. This policy also creates a rise in
466 flows between April and May that did not exist under historical uncontrolled conditions. Low flows
467 during this period are critical for creating fish spawning habitat and for exposing fertile ground for
468 planting ahead of the flood season for flood recession agriculture, so this change to the natural flow
469 pattern could have negative ecological and agricultural outcomes. Following this artificial peak,
470 the Best High Flow Policy then tends to dampen flows in the Omo River downstream of the dam,
471 as shown by the high frequency of observing flows much lower than historical minima from late

472 May to the end of August, again causing detrimental environmental flow conditions.

473 The behavior of the Best High Flow Policy in Figure 6 highlights potential drawbacks of seeking
474 to only mitigate one extreme; however the behavior of the Best Low Flow and Best Compromise
475 Policies highlights the power of multi-objective policy design in discovering favorable climate
476 adaptation strategies. The ability of these policies to reproduce the natural flow pattern under
477 climate change suggests these solutions outperform PUC on the environmental flows objective.
478 This is confirmed in Figure 7, which shows the performance of the three robust policies and PUC
479 on each of the operating objectives in each of the climate projections. Each line in this figure
480 represents a different policy, with its performance on the five objectives plotted as a function of
481 the mean annual flow or temperature in the climate projections. The favorable direction in each
482 panel is down. The climate projections are sorted from low to high flows for the hydropower,
483 environmental flows, and recession agriculture objectives, while they are sorted from low to high
484 temperatures for the sugar cane and cotton production objectives, as these are the most predictive
485 variables of performance.

486 Across panels, it can be seen that all three robust policies are almost always below PUC,
487 indicating they are performing better on nearly every objective in nearly every projection. As
488 such, the near-natural flow conditions of the low flow and compromise policy shown in Figure 6
489 also enables continued recession agriculture downstream. Furthermore, this is achieved despite
490 also drawing irrigation water for increased sugar and cotton production, and while producing a
491 clean source of power. This illustrates how well-designed multi-objective reservoir operations can
492 facilitate beneficial climate adaptation outcomes.

493 **CONCLUSIONS**

494 This study evaluates the robustness of closed-loop, nonlinear reservoir operating policies in
495 mitigating the impact of climate change on short-duration low and high flow statistics in the Omo
496 River basin. We find that tradeoffs emerge in mitigating the impacts of climate change on these
497 opposing flow extremes, as policies that best mitigate annual do poorly in reproducing annual
498 seven-day minima and vice versa. We also find that many policies replicate historical mean flows,

499 but do not necessarily reproduce extremes in the same way. This underlines the importance of
500 exploring policy performance beyond historically defined objectives when considering climate
501 change, a lesson that should be applied to other basins as well, as policies that performed similarly
502 on our environmental flows objective in the Omo River Basin had significantly different outcomes
503 for high and low flow extreme events across climate change projections.

504 However, we also demonstrate that water infrastructure development can improve climate
505 resilience, as we were able to identify compromise reservoir operating policies that produce more
506 balanced socio-ecological outcomes while mitigating the impacts of climate change on short-
507 duration high and low flow extremes. This highlights the value of multi-objective optimization
508 in producing a set of alternative operations to choose from, and in performing climate stress tests
509 to inform that selection, another recommendation applicable to other basins. Here, we were able
510 to find a compromise solution that mitigated the impacts of changing short-duration high and
511 lows flows compared to a projected uncontrolled scenario at mid-century while also improving
512 other system objectives. Many policies actually had worse robustness metrics than the projected
513 uncontrolled scenario, and simpler design procedures may have only discovered these policies.
514 Future work incorporating forecasts into the policy design could further improve performance in
515 the compromise region, as season-ahead forecasts could be used to adapt reservoir storage levels
516 up or down in a way that mitigates increasing high flows or decreasing low flows while maintaining
517 favorable socio-ecological outcomes.

APPENDIX I. OBJECTIVE FUNCTIONS

The first optimization objective was to maximize the average annual hydropower production across all reservoirs and time steps, J^{hyd} :

$$J^{hyd} = \frac{1}{A} \sum_{t=0}^{T-1} \sum_{k=1}^{K+1} \eta_k \rho g h_t^k \min(r_t^k, rMax^k) \quad (8)$$

where η_k is the efficiency of reservoir k , ρ is the density of water, g is the gravitational constant, h_t^k is the head at reservoir k on day t , r_t^k is the release from reservoir k at time t , $rMax^k$ is the turbine capacity of reservoir k , and A is 30 years. Hydropower production is summed over $K + 1$ reservoirs for the three storage dams plus Gibe III over the entire time horizon of $T = 10,957$ days (30 years from 1989-2018).

The second objective is an environmental flows objectives, J^{env} , to minimize the sum of squared deviations of simulated flows in the Omo River delta on day $t+1$, q_{t+1}^{delta} , from natural flows simulated by the SWAT model on that calendar day in absence of reservoir infrastructure, $q_{(t+1)\%365}^{natOmo}$, across all T time steps:

$$J^{env} = \frac{1}{T} \sum_{t=0}^{T-1} \left(q_{(t+1)\%365}^{natOmo} - q_{t+1}^{delta} \right)^2 \quad (9)$$

The third objective is the recession agriculture objective, defined mathematically, as minimizing the sum of squared deviations of flows in the lower Omo q_{t+1}^{LO} below a target artificial flood flow for that calendar day $q_{(t+1)\%365}^{LO}$:

$$J^{rec} = \frac{1}{T} \sum_{t=0}^{T-1} \left(\max \left(q_t^{AF} - q_{(t+1)\%365}^{LO}, 0 \right) \right)^2 \quad (10)$$

The target artificial flow for recession agriculture is 0 cms for most of the year until August 29, when it linearly increases from 240 cms to a peak of 1200 cms on September 2, where it remains until September 11, when it decreases linearly back to 0 cms on September 16.

The final two objectives, J^{sug} and J^{cot} , are to maximize sugar and cotton production, respectively, over $A = 30$ years:

541

$$J^{sug} = \frac{1}{A} \sum_{a=0}^{A-1} \sum_{s=1}^S Y_a^s \quad (11)$$

542

$$J^{cot} = \frac{1}{A} \sum_{a=0}^{A-1} \sum_{c=1}^C Y_a^c. \quad (12)$$

543 where Y_a^s is the sugar yield in sugar-growing hydrologic response unit (HRU) s in year a , and Y_a^c is

544

the yield of cotton in cotton-growing HRU c in year a .

545 **APPENDIX II. TABLES**

546 Below is the table of CMIP5 climate projections used in this study.

547

DATA AVAILABILITY STATEMENT

548

- Some code generated or used during the study are available in a repository online in accor-

549

dance with funder data retention policies: <https://github.com/sjordan29/DamReoperationOmo>

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REFERENCES

- Abbink, J. (2012). "Dam controversies: contested governance and developmental discourse on the ethiopian omo river dam." *Social anthropology*, 20(2), 125–144.
- Arnold, W., Salazar, J. Z., Carlino, A., Giuliani, M., and Castelletti, A. (2023). "Operations Eclipse Sequencing in Multipurpose Dam Planning." *Earth's Future*, 11(4), e2022EF003186 _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2022EF003186>.
- Asress, M. B., Simonovic, A., Komarov, D., and Stupar, S. (2013). "Wind energy resource development in ethiopia as an alternative energy future beyond the dominant hydropower." *Renewable and Sustainable Energy Reviews*, 23, 366–378.
- Avery, S. (2012). "Lake turkana & the lower omo: hydrological impacts of major dam and irrigation developments." *African Studies Centre, the University of Oxford*.
- Babbitt, B. (2002). "What Goes Up, May Come Down: Learning from our experiences with dam construction in the past can guide and improve dam removal in the future." *BioScience*, 52(8), 656–658 Publisher: [American Institute of Biological Sciences, Oxford University Press].
- Bates, B., Kundzewicz, Z., and Wu, S. (2008). *Climate change and water*. Intergovernmental Panel on Climate Change Secretariat.
- Bonham, N., Kasprzyk, J., Zagona, E., and Rajagopalan, B. (2024). "Subsampling and space-filling metrics to test ensemble size for robustness analysis with a demonstration in the colorado river basin." *Environmental Modelling & Software*, 172, 105933.
- Boulangé, J., Hanasaki, N., Yamazaki, D., and Pokhrel, Y. (2021). "Role of dams in reducing global flood exposure under climate change." *Nature Communications*, 12(1), 417 Bandiera_abtest: a Cc_license_type: cc_by Cg_type: Nature Research Journals Number: 1 Primary_atype: Research Publisher: Nature Publishing Group Subject_term: Climate-change impacts;Hydrology Subject_term_id: climate-change-impacts;hydrology.
- Carr, C. J. (2017). "Components of Catastrophe: Social and Environmental Consequences of Omo River Basin Development." *River Basin Development and Human Rights in Eastern Africa — A Policy Crossroads*, C. J. Carr, ed., Springer International Publishing, Cham, 75–84.

591 Chalise, D. R., Sankarasubramanian, A., and Ruhi, A. (2021). “Dams and Climate Interact to Alter
592 River Flow Regimes Across the United States.” *Earth’s Future*, 9(4), e2020EF001816 _eprint:
593 <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2020EF001816>.

594 Cole, M. A., Elliott, R. J. R., and Strobl, E. (2014). “Climate Change, Hydro-Dependency, and the
595 African Dam Boom.” *World Development*, 60, 84–98.

596 Davidson, W. (2015). “Ethiopia may ship sugar in 2016 as india-backed plant read.

597 Ehsani, N., Vörösmarty, C. J., Fekete, B. M., and Stakhiv, E. Z. (2017). “Reservoir operations under
598 climate change: Storage capacity options to mitigate risk.” *Journal of Hydrology*, 555, 435–446.

599 Ficklin, D. L., Abatzoglou, J. T., Robeson, S. M., Null, S. E., and Knouft, J. H. (2018). “Natural
600 and managed watersheds show similar responses to recent climate change.” *Proceedings of the
601 National Academy of Sciences*, 115(34), 8553–8557 Publisher: Proceedings of the National
602 Academy of Sciences.

603 Ficklin, D. L., Null, S. E., Abatzoglou, J. T., Novick, K. A., and Myers,
604 D. T. (2022). “Hydrological Intensification Will Increase the Complexity
605 of Water Resource Management.” *Earth’s Future*, 10(3), e2021EF002487 _eprint:
606 <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2021EF002487>.

607 Flecker, A. S., Shi, Q., Almeida, R. M., Angarita, H., Gomes-Selman, J. M., García-Villacorta,
608 R., Sethi, S. A., Thomas, S. A., Poff, N. L., Forsberg, B. R., et al. (2022). “Reducing adverse
609 impacts of amazon hydropower expansion.” *Science*, 375(6582), 753–760.

610 Fratkin, E. (2014). “Ethiopia’s pastoralist policies: development, displacement and resettlement.”
611 *Nomadic Peoples*, 18(1), 94–114.

612 Gao, Y., Vogel, R. M., Kroll, C. N., Poff, N. L., and Olden, J. D. (2009). “Development of
613 representative indicators of hydrologic alteration.” *Journal of Hydrology*, 374(1), 136–147.

614 Giuliani, M., Anghileri, D., Castelletti, A., Vu, P. N., and Soncini-Sessa, R. (2016a). “Large storage
615 operations under climate change: expanding uncertainties and evolving tradeoffs.” *Environmental
616 Research Letters*, 11(3), 035009.

617 Giuliani, M., Castelletti, A., Pianosi, F., Mason, E., and Reed, P. M. (2016b). “Curses, tradeoffs, and

618 scalable management: Advancing evolutionary multiobjective direct policy search to improve
619 water reservoir operations.” *Journal of Water Resources Planning and Management*, 142(2),
620 04015050.

621 Giuliani, M., Zaniolo, M., Sinclair, S., Micotti, M., Van Orshoven, J., Burlando, P., and Castelletti,
622 A. (2022). “Participatory design of robust and sustainable development pathways in the Omo-
623 Turkana river basin.” *Journal of Hydrology: Regional Studies*, 41, 101116.

624 Goodland, R. (2010). “The World Bank Versus the World Commission on Dams.” 3(2), 15.

625 Graf, W. L. (2001). “Dam age Control: Restoring the Physical Integrity of America’s Rivers.”
626 *Annals of the Association of American Geographers*, 91(1), 1–27.

627 Gyasi, S. F., Boamah, B., Awuah, E., and Otabil, K. B. (2018). “A Perspective Analysis of Dams
628 and Water Quality: The Bui Power Project on the Black Volta, Ghana.” *Journal of Environmental
629 and Public Health*, 2018, 6471525.

630 Hadka, D. and Reed, P. (2013). “Borg: An auto-adaptive many-objective evolutionary computing
631 framework.” *Evolutionary computation*, 21(2), 231–259.

632 Hadka, D. and Reed, P. (2015). “Large-scale parallelization of the Borg multiobjective evolution-
633 ary algorithm to enhance the management of complex environmental systems.” *Environmental
634 Modelling & Software*, 69(C), 353–369.

635 Hall, J. W., Grey, D., Garrick, D., Fung, F., Brown, C., Dadson, S. J., and Sadoff, C. W. (2014).
636 “Coping with the curse of freshwater variability.” *Science*, 346(6208), 429–430.

637 Hatchard, S., Schmitt, R. J., Pianosi, F., Savage, J., and Bates, P. (2023). “Strategic siting and
638 design of dams minimizes impacts on seasonal floodplain inundation.” *Environmental Research
639 Letters*.

640 Hathaway, T. (2009). “Facing gibe 3 dam: Indigenous communities of ethiopia’s lower omo valley.”
641 *International Rivers*.

642 Herman, J. D., Reed, P. M., Zeff, H. B., and Characklis, G. W. (2015). “How should robustness be
643 defined for water systems planning under change?.” *Journal of Water Resources Planning and
644 Management*, 141(10), 04015012.

645 Ho, M., Lall, U., Allaire, M., Devineni, N., Kwon, H. H., Pal, I., Raff, D., and Wegner, D. (2017).
646 “The future role of dams in the United States of America.” *Water Resources Research*, 53(2),
647 982–998 _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2016WR019905>.

648 Hodbod, J., Stevenson, E. G., Akall, G., Akuja, T., Angelei, I., Bedasso, E. A., Buffavand, L.,
649 Derbyshire, S., Eulenberger, I., Gownaris, N., et al. (2019). “Social-ecological change in the
650 omo-turkana basin: A synthesis of current developments.” *Ambio*, 48(10), 1099–1115.

651 Human Rights Watch (2017). “Ethiopia: Dams, plantations a threat to kenyans.

652 Huntington, T. G. (2006). “Evidence for intensification of the global water cycle: Review and
653 synthesis.” *Journal of Hydrology*, 319(1-4), 83–95.

654 Hurford, A. P. and Harou, J. J. (2014). “Balancing ecosystem services with energy and food
655 security – Assessing trade-offs from reservoir operation and irrigation investments in Kenya’s
656 Tana Basin.” *Hydrology and Earth System Sciences*, 18(8), 3259–3277.

657 IEA (2016). “Electricity access database.” International Energy Agency.

658 IUCN Water (2019). “The future of dams: Viable options or stranded assets.

659 Johnston, L. (2009). “Ethiopia - gibe iii hydropower project. trip report.

660 Jordan, S., Quinn, J., Zaniolo, M., Giuliani, M., and Castelletti, A. (2022). “Advancing reservoir
661 operations modelling in SWAT to reduce socio-ecological tradeoffs.” *Environmental Modelling
662 & Software*, 157, 105527.

663 Kasprzyk, J. R., Nataraj, S., Reed, P. M., and Lempert, R. J. (2013). “Many objective robust decision
664 making for complex environmental systems undergoing change.” *Environmental Modelling &
665 Software*, 42, 55–71.

666 Kendall, M. G. (1948). “Rank correlation methods.

667 Kroll, C. N., Croteau, K. E., and Vogel, R. M. (2015). “Hypothesis tests for hydrologic alteration.”
668 *Journal of Hydrology*, 530, 117–126.

669 Liermann, C. R., Nilsson, C., Robertson, J., and Ng, R. Y. (2012). “Implications of Dam Obstruction
670 for Global Freshwater Fish Diversity.” *BioScience*, 62(6), 539–548.

671 Lumbroso, D. M., Woolhouse, G., and Jones, L. (2015). “A review of the consideration of climate

672 change in the planning of hydropower schemes in sub-Saharan Africa.” *Climatic Change*, 133(4),
673 621–633.

674 Mann, H. B. (1945). “Nonparametric tests against trend.” *Econometrica: Journal of the econometric*
675 *society*, 245–259.

676 Markonis, Y., Papalexiou, S. M., Martinkova, M., and Hanel, M. (2019). “Assessment of
677 Water Cycle Intensification Over Land using a Multisource Global Gridded Precipitation
678 DataSet.” *Journal of Geophysical Research: Atmospheres*, 124(21), 11175–11187 _eprint:
679 <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019JD030855>.

680 McPhail, C., Maier, H., Westra, S., Kwakkel, J., and Van Der Linden, L. (2020). “Impact of scenario
681 selection on robustness.” *Water Resources Research*, 56(9), e2019WR026515.

682 Mittal, N., Bhawe, A. G., Mishra, A., and Singh, R. (2016). “Impact of Human Intervention and
683 Climate Change on Natural Flow Regime.” *Water Resources Management*, 30(2), 685–699.

684 Mueller, M. (2007). “Adapting to climate change: water management for urban resilience - Mike
685 Muller, 2007, <<https://journals.sagepub.com/doi/abs/10.1177/0956247807076726>>.

686 Oakland Institute (2011). “Understanding land investment deals in africa, half a million lives
687 threatened by land development for sugar plantations in lower omo.

688 Olden, J. D., Konrad, C. P., Melis, T. S., Kennard, M. J., Freeman, M. C., Mims, M. C., Bray, E. N.,
689 Gido, K. B., Hemphill, N. P., Lytle, D. A., McMullen, L. E., Pyron, M., Robinson, C. T., Schmidt,
690 J. C., and Williams, J. G. (2014). “Are large-scale flow experiments informing the science and
691 management of freshwater ecosystems?.” *Frontiers in Ecology and the Environment*, 12(3),
692 176–185 _eprint: <https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1890/130076>.

693 Poff, N. L., Brown, C. M., Grantham, T. E., Matthews, J. H., Palmer, M. A., Spence, C. M., Wilby,
694 R. L., Haasnoot, M., Mendoza, G. F., Dominique, K. C., and Baeza, A. (2016). “Sustainable
695 water management under future uncertainty with eco-engineering decision scaling.” *Nature*
696 *Climate Change*, 6(1), 25–34 Bandiera_abtest: a Cg_type: Nature Research Journals Number:
697 1 Primary_atype: Reviews Publisher: Nature Publishing Group Subject_term: Climate-change
698 ecology Subject_term_id: climate-change-ecology.

699 Poff, N. L. and Hart, D. D. (2002). “How Dams Vary and Why It Matters for the Emerging
700 Science of Dam Removal: An ecological classification of dams is needed to characterize how
701 the tremendous variation in the size, operational mode, age, and number of dams in a river
702 basin influences the potential for restoring regulated rivers via dam removal.” *BioScience*, 52(8),
703 659–668.

704 Quinn, J., Hadjimichael, A., Reed, P., and Steinschneider, S. (2020). “Can exploratory modeling
705 of water scarcity vulnerabilities and robustness be scenario neutral?.” *Earth’s Future*, 8(11),
706 e2020EF001650.

707 Reis, J. and Shortridge, J. (2020). “Impact of uncertainty parameter distribution on robust decision
708 making outcomes for climate change adaptation under deep uncertainty.” *Risk Analysis*, 40(3),
709 494–511.

710 Riggs, H. (1980). “Characteristics of low flows.” *Journal of the Hydraulics Division*, 106(5),
711 717–731.

712 Sabo, J. L., Ruhi, A., Holtgrieve, G. W., Elliott, V., Arias, M. E., Ngor, P. B., Räsänen, T. A., and
713 Nam, S. (2017). “Designing river flows to improve food security futures in the Lower Mekong
714 Basin.” *Science*, 358(6368), eaao1053.

715 Schmitt, R. J., Bizzi, S., Castelletti, A., and Kondolf, G. (2018). “Improved trade-offs of hydropower
716 and sand connectivity by strategic dam planning in the mekong.” *Nature Sustainability*, 1(2),
717 96–104.

718 Schneller, G. and Sphicas, G. (1983). “Decision making under uncertainty: Starr’s domain crite-
719 rion.” *Theory and Decision*, 15(4), 321–336.

720 Starr, M. (1963). “Product design and decision theory, prentical hall.” *Inc., Englewoods, NJ*.

721 Sundin, C. (2017). “Exploring the water-energy nexus in the omo river basin: a first step toward
722 the development of an integrated hydrological-osemosys energy model.

723 Tiwari, H., Rai, S. P., Sharma, N., and Kumar, D. (2017). “Computational approaches for annual
724 maximum river flow series.” *Ain Shams Engineering Journal*, 8(1), 51–58.

725 Trenberth, K. E. (2011). “Changes in precipitation with climate change.” *Climate Research*, 47(1-2),

726 123–138.

727 van Oorschot, M., Kleinhans, M., Buijse, T., Geerling, G., and Middelkoop, H. (2018). “Combined
728 effects of climate change and dam construction on riverine ecosystems.” *Ecological Engineering*,
729 120, 329–344.

730 Watts, R. J., Richter, B. D., Opperman, J. J., and Bowmer, K. H. (2011). “Dam reoperation in an
731 era of climate change.” *Marine and Freshwater Research*, 62(3), 321–327 Publisher: CSIRO
732 PUBLISHING.

733 Whipple, A. A. and Viers, J. H. (2019). “Coupling landscapes and river flows to re-
734 store highly modified rivers.” *Water Resources Research*, 55(6), 4512–4532 _eprint:
735 <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2018WR022783>.

736 Wild, T. B., Reed, P. M., Loucks, D. P., Mallen-Cooper, M., and Jensen, E. D. (2019). “Balancing
737 Hydropower Development and Ecological Impacts in the Mekong: Tradeoffs for Sambor Mega
738 Dam.” *Journal of Water Resources Planning and Management*, 145(2), 05018019 Publisher:
739 American Society of Civil Engineers.

740 Woodrooffe, R. (1996). “Omo-gibe river basin integrated development master plan study final report
741 vol. iii.” *VI Water resources Surveys and Inventories, ministry of Water Resources, Addis Ababa*.

742 Yun, X., Tang, Q., Wang, J., Liu, X., Zhang, Y., Lu, H., Wang, Y., Zhang, L., and Chen, D. (2020).
743 “Impacts of climate change and reservoir operation on streamflow and flood characteristics in
744 the Lancang-Mekong River Basin.” *Journal of Hydrology*, 590, 125472.

745 Zaniolo, M., Giuliani, M., Bantider, A., and Castelletti, A. (2021a). “Hydropower development:
746 Economic and environmental benefits and risks.” *The Omo-Turkana Basin*, Routledge. Num
747 Pages: 21.

748 Zaniolo, M., Giuliani, M., Sinclair, S., Burlando, P., and Castelletti, A. (2021b). “When timing
749 matters—misdesigned dam filling impacts hydropower sustainability.” *Nature Communications*,
750 12(1), 3056 Number: 1 Publisher: Nature Publishing Group.

751 Zarfl, C., Lumsdon, A. E., Berlekamp, J., Tydecks, L., and Tockner, K. (2015). “A global boom in
752 hydropower dam construction.” *Aquatic Sciences*, 77(1), 161–170.

753 Zeff, H. B., Herman, J. D., Reed, P. M., and Characklis, G. W. (2016). “Cooperative
754 drought adaptation: Integrating infrastructure development, conservation, and water trans-
755 fers into adaptive policy pathways.” *Water Resources Research*, 52(9), 7327–7346 _eprint:
756 <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2016WR018771>.

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List of Tables

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1 Climate projections 35

TABLE 1. CMIP5 climate projections used in the study

Model	RCP			
	2.6	4.5	6.0	8.5
ACCESS 1.0	-	✓	-	✓
CCSM4	-	✓	✓	✓
CESM1-BGC	-	✓	-	✓
CMCC-CESM	-	-	-	✓
CMCC-CMS	-	✓	-	✓
CMCC-CM5	✓	✓	-	-
CSIRO-Mk3.6.0	✓	✓	✓	✓
GFDL-CM3	✓	-	✓	✓
GFDL-ESM2G	✓	✓	✓	✓
GFDL-ESM2M	✓	✓	✓	✓
HadGEM2-CC	-	✓	-	✓
HadGEM2-ES	-	-	✓	-
MIROC-ESM-CHEM	✓	✓	✓	✓
MIROC-ESM	✓	✓	✓	✓
MPI-ESM-LR	✓	✓	-	✓
MPI-ESM-MR	✓	✓	-	✓
NorESM-M	✓	✓	✓	✓

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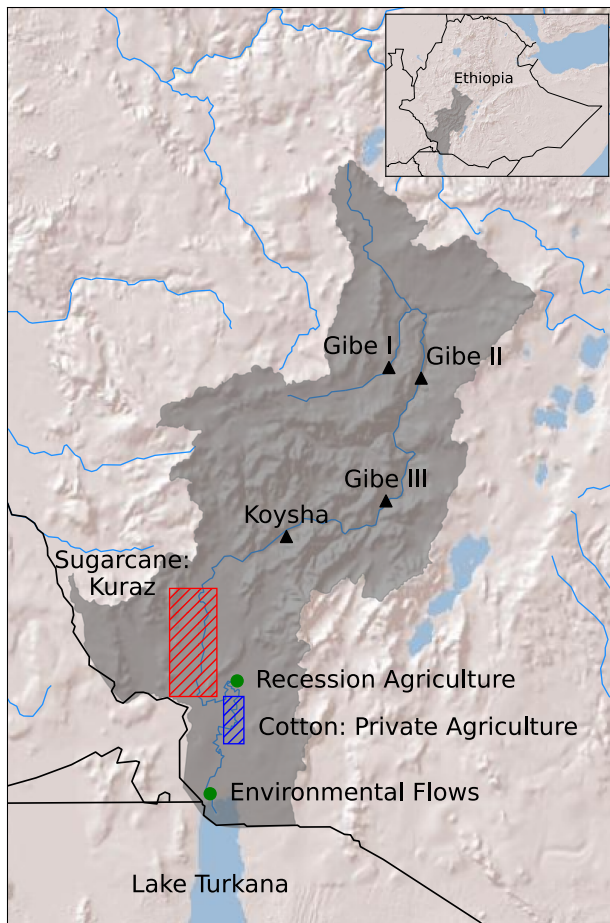


Fig. 1. Map of the Omo River Basin and its hydroelectric dams (existing and under construction), as well as the different stakeholders they serve: private sugarcane and cotton agriculture, indigenous recession agriculture, and environmental flows. Figure adapted from [Jordan et al. \(2022\)](#).

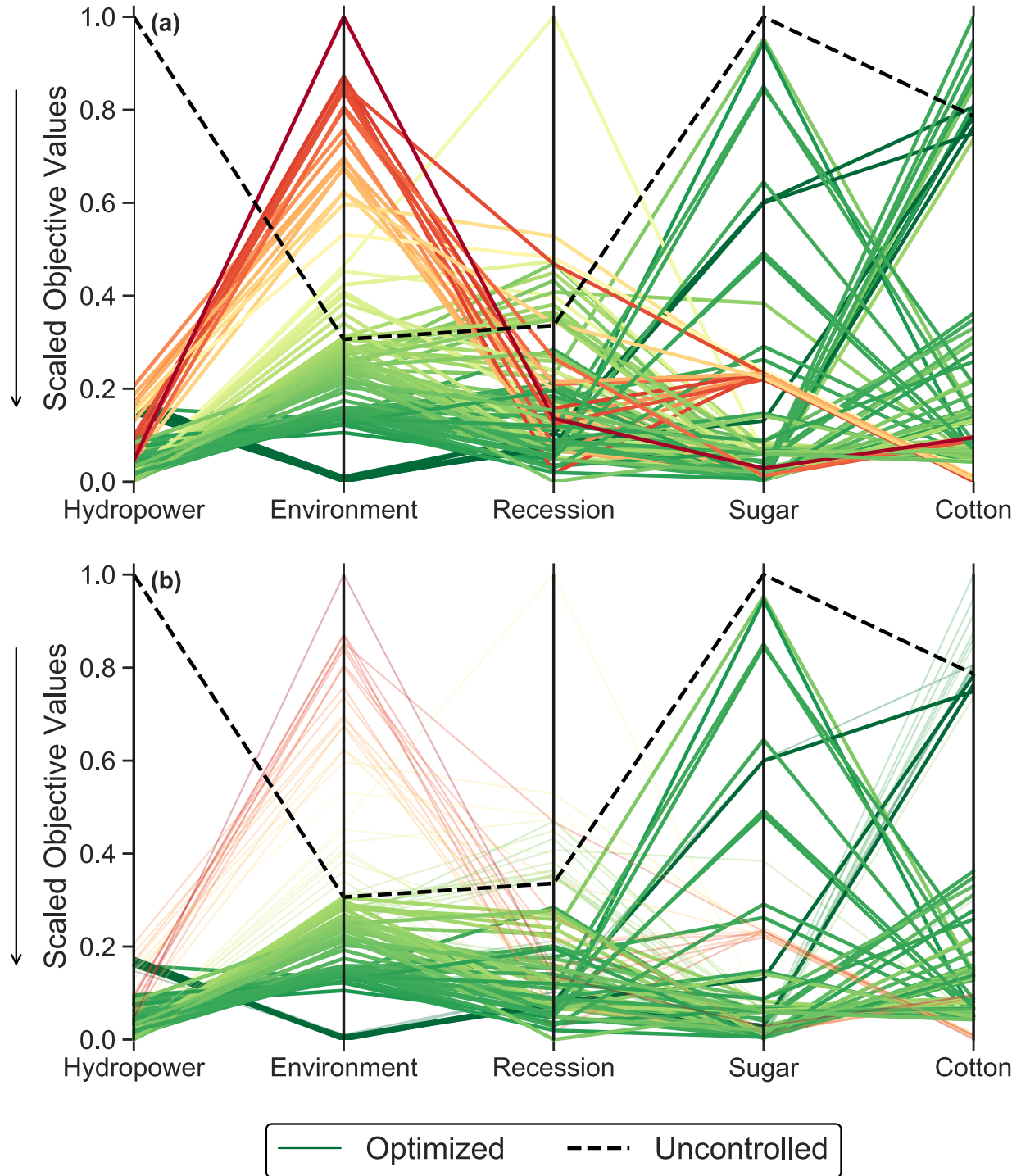


Fig. 2. (a) Parallel axis plots showing historical tradeoffs of operating policies under historical conditions. (b) The same parallel axis plot, but with policies that are outperformed by the historical uncontrolled conditions on at least one objective shown as transparent, and policies that outperform historical uncontrolled conditions on all objectives as opaque.

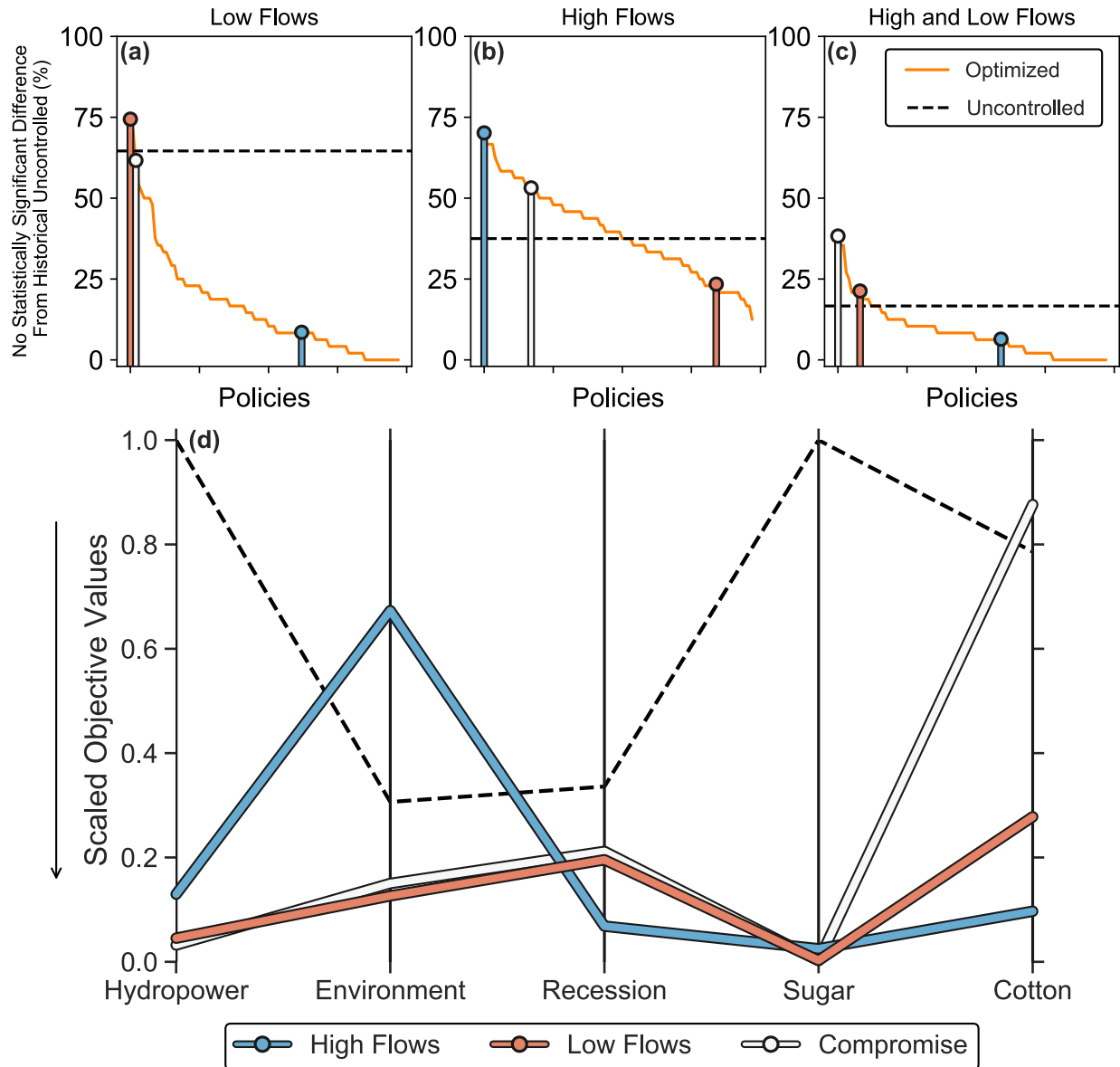


Fig. 3. (a) - (c) Performance on robustness metrics of all policies, sorted from highest to lowest on (a) 7QS, (b) AMS, and (c) both 7QS and AMS with policies that perform best on each metric highlighted. Policies with robustness metrics that are higher than the projected uncontrolled scenario (PUC) mitigate the impact of climate change while those with lower metrics exacerbate the impact of climate change. (d) Parallel axis plot showing historical tradeoffs of operating policies under historical conditions. Robust policies analyzed more deeply are highlighted.

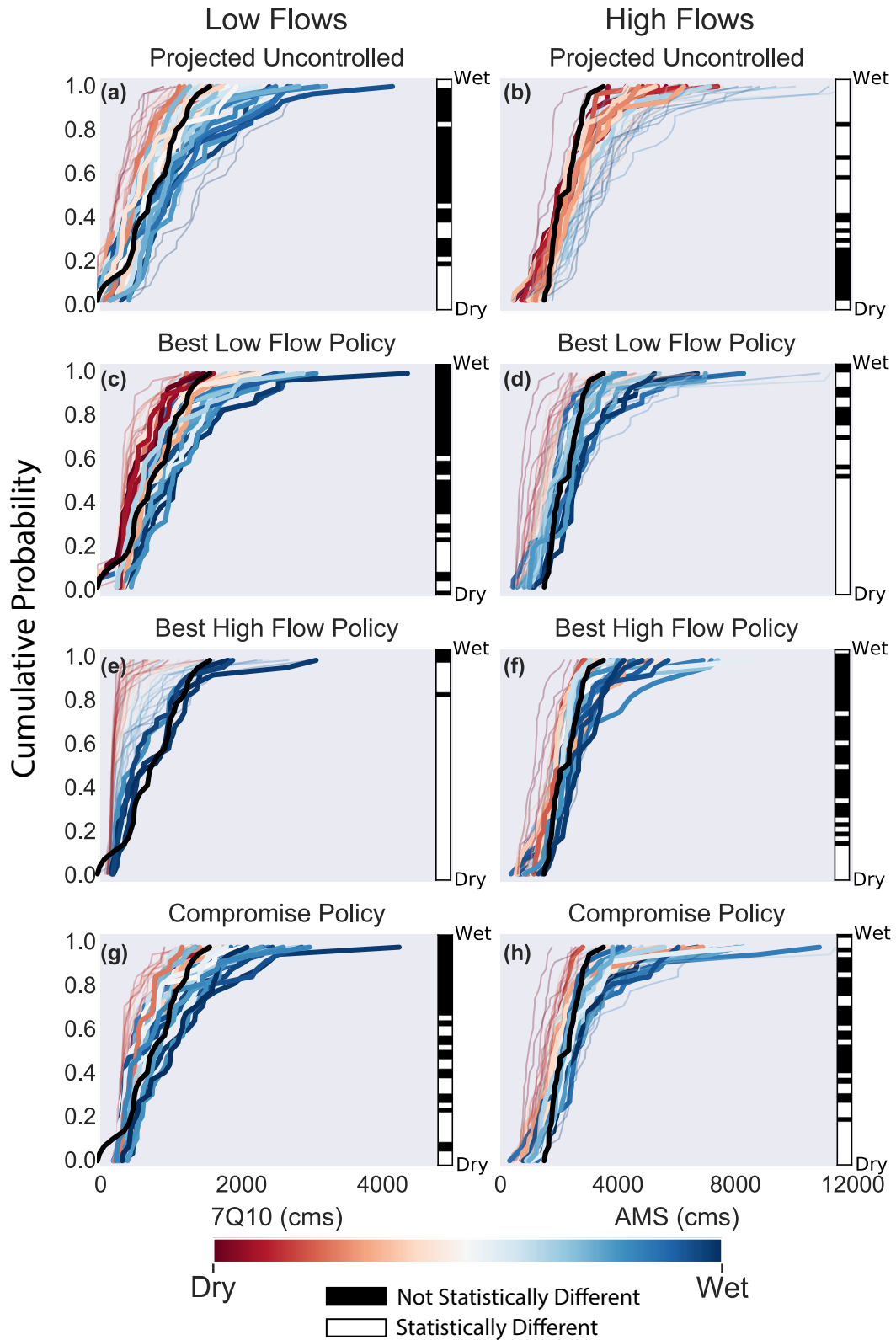


Fig. 4. Empirical cumulative distributions of seven-day low flows (left column) and annual maxima series (right column) for (a,b) projected uncontrolled conditions, (c,d) the Best Low Flow Policy, (e,f) the Best High Flow Policy, and (g,h) the Best Compromise Policy. The ECDFs of historical uncontrolled high and low flows are shown in black on each plot.

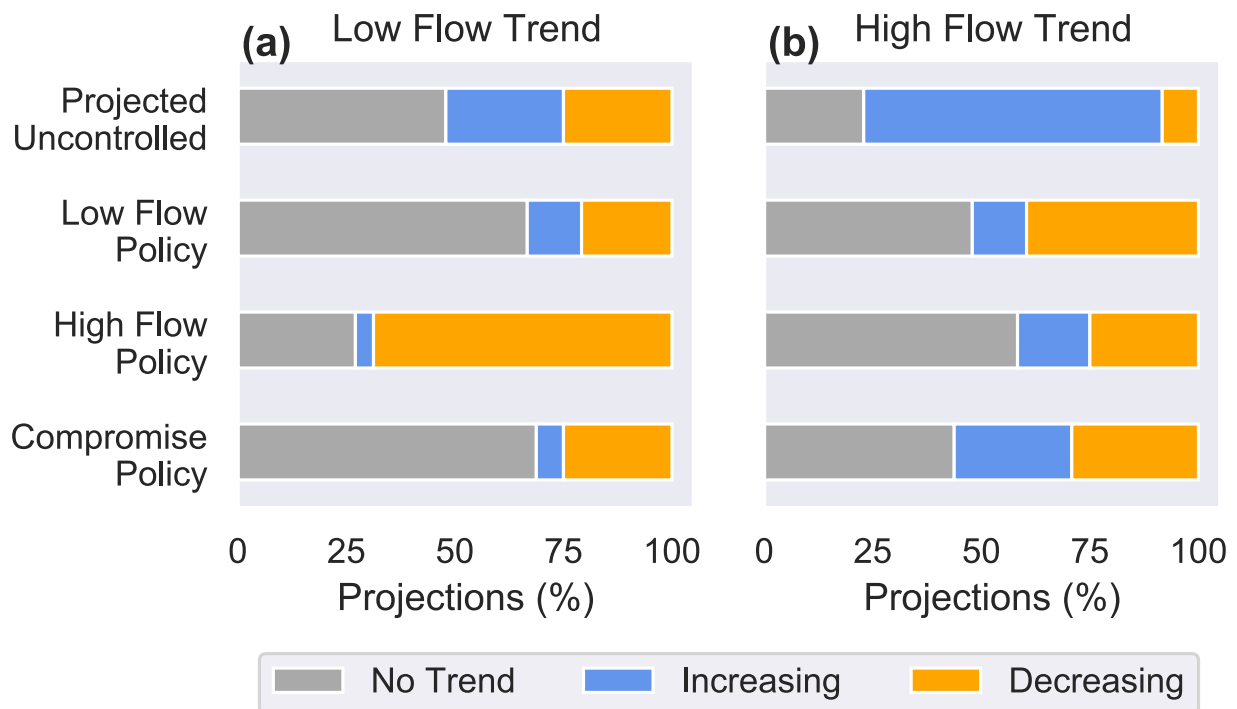


Fig. 5. Breakdown of the percent of projections that show no trend, an increasing trend, or decreasing trend for a projected uncontrolled scenario as well as for the best policy for preserving low flows, the best policy for preserving high flows, and the compromise policy that best preserves both high and low flows for (a) seven-day low flows, and (b) annual maxima series.

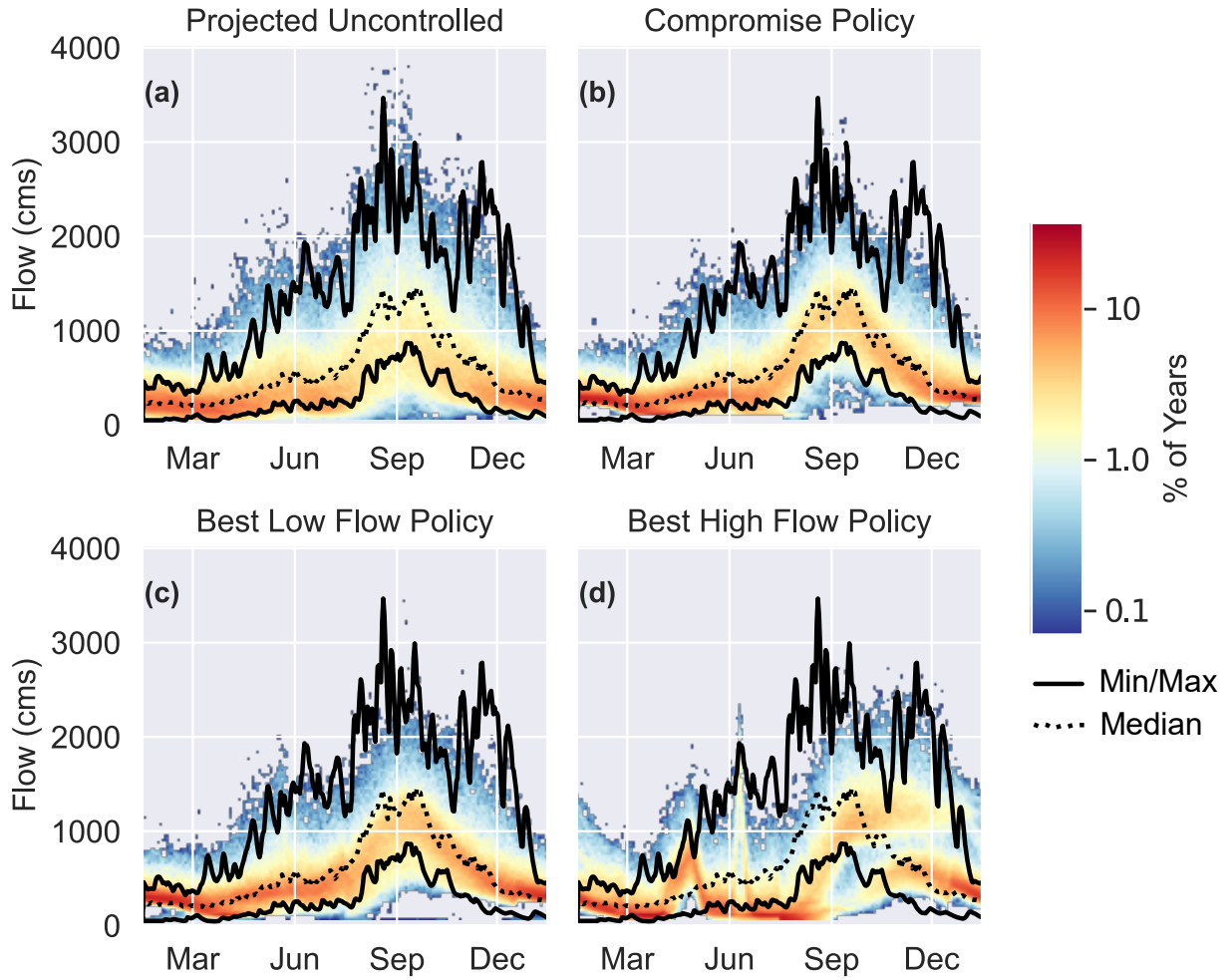


Fig. 6. The percent of simulated years where the flow was at different magnitudes on each calendar day, with high frequencies in red and low frequencies in blue for (a) a projected uncontrolled scenario, (b) the compromise policy (c) the best policy for preserving low flows, and (d) the best policy for preserving high flows. Maximum and minimum daily HUC flows are shown with the black solid line and the median daily HUC flows are represented by a dotted black line.

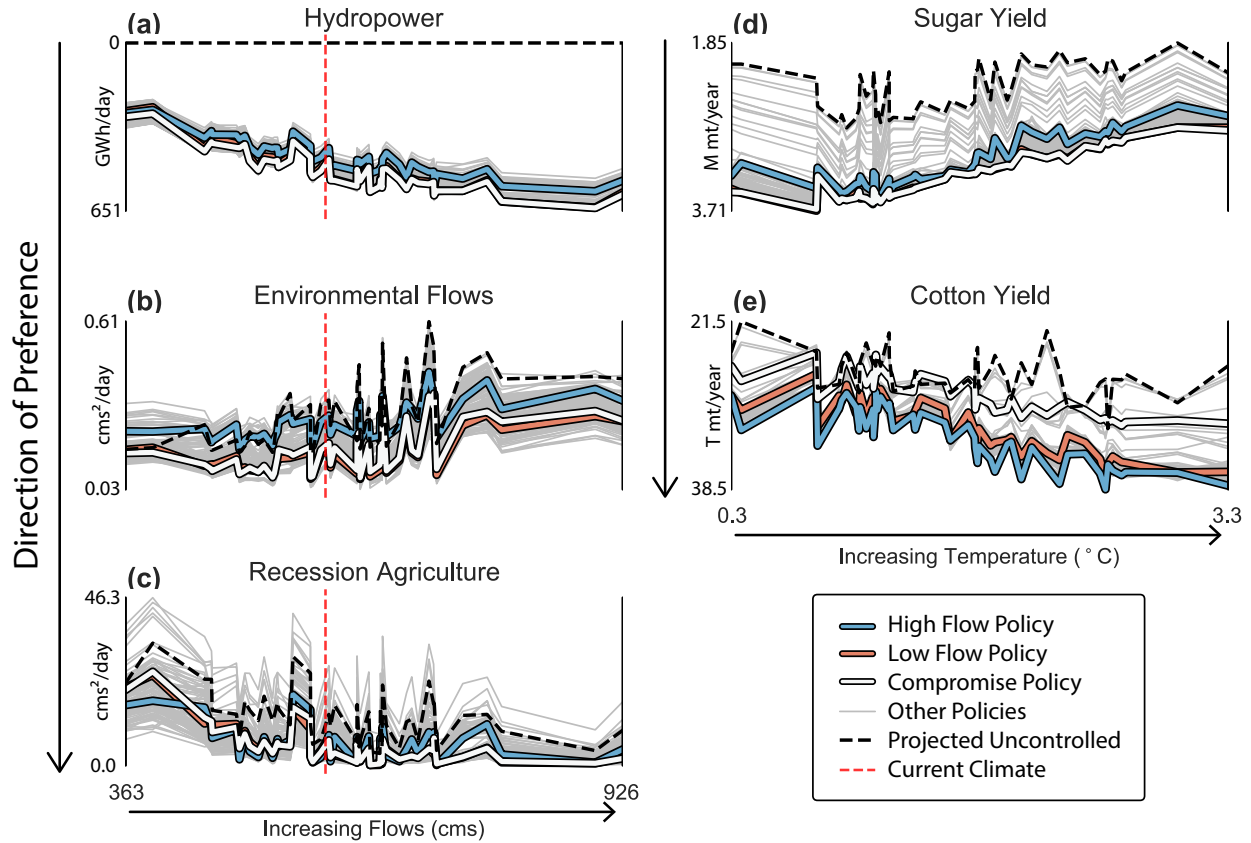


Fig. 7. Performance of the robust policies in 48 climate projections on (a) hydropower, (b) environmental flows, (c) recession agriculture, (d) sugar yield and (e) cotton yield (the remaining policies are shown in light gray). Projected average flows range from 363.4 to 926.1 cms, while historical average flows were 590 cms, denoted by the dashed red line in a-c. Projections that fall to the left of the red line are projected to be drier on average than the historical record, while those to the right are projected to be wetter. Temperatures are projected to increase between 0.26 to 3.34 degrees Celsius compared to historical temperatures. With a few exceptions, the robust policies generally perform better than the projected uncontrolled scenario across all climate projections.