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Research papers

Addressing climate uncertainty and incomplete information in transboundary river treaties: A scenario-neutral dimensionality reduction approach

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ABSTRACT

Climate change will alter the flow availability and expected water allocations in international river treaties, many of which were designed using historical flow records. Effective transboundary treaties should anticipate these concerns and seek to satisfy the priorities of all riparian countries while being robust to impending changes in climate. This task is complicated by the fact that specific objectives associated with each party's priorities are not necessarily common knowledge (framing uncertainty), and the direction, amplitude and effect of long term changes in hydro-climatic drivers can be highly uncertain (climate uncertainty).

We frame the design of a transboundary treaty as a multi-objective optimization problem. We use hierarchical clustering to address problem-framing uncertainty by identifying the subset of objectives associated with the governing trade-offs imposed by the bio-physical characteristics of the shared river system. We then carry out a scenario-neutral climate sensitivity analysis to identify climate-robust Pareto-optimal treaty solutions. We illustrate the approach for the Ganges water agreement, which is due to be renewed in 2026. Based on an enumerated population of 25,121 feasible treaty solutions, we identify governing objectives and 16 treaty solutions that are Pareto optimal under most considered combinations of changes in sea level and dry season flow regime. This work provides a path towards improving transboundary allocations for the Ganges water treaty and, more broadly, a template to support transboundary cooperation over shared international rivers.

1. Introduction

Climate change and increased anthropogenic water use threaten water security and pose challenges for water management in many basins around the world. Stronger storms (Chen et al., 2020), more intense droughts (Overpeck and Udall, 2020), and greater hydro-meteorological uncertainty (Panahi et al., 2020) are expected in many regions of the world, where population growth combined with agricultural intensification will further threaten water security. The consequences of these changes include groundwater depletion (Cotterman et al., 2018), freshwater and soil salinization (Haque, 2006), loss of livelihoods (Muringai et al., 2019) and other environmental crises (Turner et al., 2020). These issues are particularly evident in several internationally shared basins, including the Nile (Beyene et al., 2010), Mekong(Kiem et al., 2008), Colorado (Barnett and Pierce, 2009) and Ganges (Rahman et al., 2019) rivers. Stable and effective policy instruments to manage transboundary waters have become critical for maintaining international cooperation and preventing economic or political crises (Dinar et al., 2016). Over two hundred transboundary river basins have been identified, housing 42% of the global population. Water sharing in these basins has led to the creation of over six hundred treaties on freshwater management since the early nineteenth century (UNEP-DHI, UNEP, 2016). However, many of these agreements may not perform well under an increasingly volatile and uncertain climate (Draper and Kundell, 2007). New or renegotiated agreements should ideally balance the competing needs of each party while striving to support benefits that are robust to a changing climate.

This process can be formulated as a multi-objective optimization

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problem that riparian countries cooperatively solve. Following the framework in Maier et al. (2019), the objectives (i.e. outcomes of interest) are to maximize environmental, social and economic benefits and to minimize environmental, social and economic costs by selecting appropriate transboundary flow allocation rules, which are the decision variables. The set of objectives considered in the optimization corresponds to the union of the sets of objectives associated with each party. This formulation allows us to focus on conflicting objectives in terms of tradeoffs between measures of system performance. This notion of conflict does not necessarily correspond to conflicting actor incentives as treated by non-cooperative game theory [see, e.g., (Müller et al., 2017; Penny et al., 2021)]. Indeed, the considered tradeoffs between measures of system performance can also arise for a single actor with conflicting performance objective measures. For example, a given actor might want to simultaneously minimize the peak and maximize the average of incoming streamflow.The constraints include the available water resources, the physical limits on the diversion infrastructure, political feasibility and historical legacies (e.g., pre-existing treaties). A solution consists of the set of transboundary flow allocation rules that form a treaty. Trade-offs associated with the potentially conflicting nature of the objectives are captured by the notion of Pareto-optimality [e. g., Kasprzyk et al., 2013]. A solution is Pareto-optimal if no change in the decision variables could improve any objective without making the situation worse for another. In contrast, a solution that is not Pareto optimal would miss some of the possible joint gains of cooperation and leaves on the table one or more solutions that would make all parties better off (Kronaveter and Shamir, 2009). Pareto-optimality is therefore a requisite attribute of cooperative bargaining solutions (Nash, 1953; Kalai and Smorodinsky, 1975), and a desirable outcome for international water negotiations (Kronaveter and Shamir, 2009).

In reality, of course, transboundary water negotiations might not be cooperative and problem-framing uncertainties arise from the fact that not all relevant optimization objectives are common knowledge across the negotiating parties. Our approach relies on the assumption that an initial broad set of candidate objectives can generally be constructed intuitively based on the bio-physical and socio-political context (see discussion in Section 4.1). For example, in the context of the Ganges, both parties likely seek to maximize average flow availability during the dry season, but minimize salinity and flow variability. These candidate objectives might be refined using information available to both parties (though not necessarily to the wider public) though appropriate approaches to engage stakeholders in a process of knowledge co-production (Wyborn et al., 2019). However, the relative importance of each objective for each party (i.e. objectives that matter vs. objectives that can be safely removed from the optimization) might ultimately be kept private for strategic reasons. In other words, the true set of optimization objectives is likely unknown, which prevents the true set of Pareto-optimal solutions from being discovered. This issue is well known in the negotiation literature, where a variety of protocols have been proposed to guide the negotiating parties towards the discovery and achievement of Pareto-optimal outcomes [see, e.g., (Ehtamo et al., 1999; Lai and Sycara, 2009; Kronaveter and Shamir, 2009)]. Here, in contrast, we seek to decrease the dimensionality of the set of candidate objectives *ex ante*, based on (known) dynamics of the bio-physical system, rather than (publicly unknown) preferences of the negotiating parties. Doing so does not necessarily reveal the true set of hidden stakeholder objectives. Rather, the approach can be seen as a way to leverage publicly available information to simplify a many-objective optimization problem that is poorly framed due to hidden objectives (see Section 4.4)

Pareto optimality is a non-dominance mathematical partitioning rule. As one increases the number of objectives, the partitioning rule becomes less discriminatory, resulting in an increase in the size of the Pareto optimal set – a phenomenon known as dominance resistance [e. g., (Reed et al., 2013)]. An excessively large set of objectives (such as the full set of initial candidate objectives) will cause many solutions that are non-dominant under the true set of objectives to be included in the discriminated solution set. In contrast, considering too few objectives can lead to the opposite issue of oversimplifying the problem by missing important portions of the objective set that are only non-dominated with the addition of more objectives [see examples in (Kollat and Reed, 2007; Woodruff et al., 2013)]. Our contribution is to leverage the internal physical dynamics of the system to navigate this trade-off. We apply a data-based pattern recognition technique (hierarchical clustering) on enumerated solutions to reduce the dimensionality of the set of objectives and approximate the Pareto-optimal set of solutions, while minimizing information loss (see discussion in Section 4.2). In doing so, we assume that all feasible treaty solutions can be enumerated, an assumption that is discussed in Section 4.3. Our approach relates to the literature seeking to reduce the complexity of many-objective optimization problems by exploiting the correlation between certain objectives [e.g., (Deb et al., 2006; Brockhoff and Zitzler, 2006; Brockhoff and Zitzler, 2009)]. For example, Giuliani et al. (2014) leverages numerical correlations between objectives to aggregate them into a reduced number of linear combinations of objectives (principal components), with respect to which the optimization problem is solved. Here, we follow Lindroth et al. (2010), and estimate Pearson correlation coefficients across enumerated solutions between pairs of objectives. We then use a clustering procedure to systematically reduce the number of objectives in a manner that is informed by the structure of these correlations in the underlying dataset.

Another type of uncertainty, this time on the future states of the world, arises from the fact that it is challenging to determine precisely how much and how quickly the relevant climate inputs will change (Deser et al., 2012). In that context, it is not sufficient to identify water allocations that are Pareto-optimal under current conditions. Rather, the analysis must also navigate the trade-off between objectives under a range of potential changes in environmental constraints. We incorporate a scenario-neutral sensitivity analysis to evaluate the robustness of the Pareto-optimal set of solutions to different combinations of climate inputs. Following Brown et al. (2012), different components of the system are considered to create a model with a climate response function. The model is then perturbed by stochastically generated climate inputs, in order to identify the climate states associated with high risk of systemic failure. Despite the caveats discussed in Section 4.5 this type of scenario-neutral analysis is commonly used to evaluate the climate vulnerability of systems (Brown et al., 2012; Jones, 2001; Wilby and Dessai, 2010) (including transboundary river systems (De Boer et al., 2021)) in situations where the change in the relevant climatic drivers is highly uncertain. However, it has not (to our knowledge) been applied to evaluate the effect of climate uncertainty on the composition of Pareto-optimal solution sets.

The approach that we propose, which combines hierarchical clustering and scenario neutral analysis, falls within the broader category of exploratory modelling approaches, in the sense that it addresses both types of uncertainty (on framing and on future world states) by using numerical simulation to systematically explore their implications on enumerated outcomes. It fits within recent frameworks to confront deep uncertainty within water management problems through robust multi-objective optimization [see, Moallemi et al., 2020 Table 1]. For example, Kasprzyk et al. (2012) proposes an iterative framework where a pre-processing analysis (Sobol' variance decomposition) is carried out

Table 1
Decision Variables.

Parameter	Current Treaty	Feasible Range	Enum. Increment
p_{Q1} (%)	50	$[45, 70]$	1
Q_2 ($\times$ 1000 cusec)	35	$[30, 40]$	1
Q_{int} ($\times$ 1000 cusec)	35	$[25, 40]$	1
m (periods)	6	$[0, 10]$	2
n (days)	10	$[0, 15]$	5

to reformulate the problem *de Novo* in a way that seeks to balance complexity and effectiveness before the multi-objective optimization. In a similar manner, we use hierarchical clustering here to refine an initial vector of candidate objectives to update the dimensionality of the problem before identifying Pareto-optimal solutions. Kasprzyk et al. (2012) continues with a scenario analysis to test the robustness of solutions to model assumptions – a step that mirrors our proposed scenario-neutral analysis.

We demonstrate our combined approach using the Ganges Water Sharing Agreement (GWSA) between India and Bangladesh as an illustrative example. The agreement determines the flow of the Ganges into Bangladesh during the dry season (January-May) by regulating the operation of the Farakka barrage (Fig. 1) in India, approximately 100 km upstream of the border. The barrage diverts Ganges river water into the Bhagirathi-Hooghly river, a distributary of the Ganges that discharges into the Bay of Bengal in India, near the port city of Kolkata. The GWSA exemplifies the multi-faceted challenges associated with transboundary river management under a changing climate. The treaty was signed in 1996, with the purpose of balancing flow requirements to de-silt the port of Kolkata – one of India's major cargo ports – with dry season irrigation and environmental water needs in Bangladesh (Tanzeema and Faisal, 2001). Since then, the flow regime of the Ganges and the geomorphology of the delta have changed substantially under the coupled effect of changing rain patterns and upstream water uses (Rahman et al., 2000). In addition, salt intrusion has become a major concern throughout the Ganges delta, due in part to sea level rise and increasingly frequent and intense storm surges (Rahman et al., 2019). These changes have had particularly damaging economic, public health and ecological impact in coastal communities in South-Western Bangladesh and the Sundarbans, a unique (and world's largest) mangrove ecosystem (Faisal and Parveen, 2004). Sufficient provision of freshwater inflow through the Ganges is paramount to prevent saline intrusions (Rahman et al., 2000; Pethick and Orford, 2013; Shammi et al., 2016). These rapidly changing conditions might have reduced the effectiveness of current treaty allocations (Penny et al., 2020), which were based on average flow data collected from 1949 – 1988 and have not been updated (Salman and Uprety, 1999). Because the treaty is slated to be renewed in 2026, a tractable approach to understand and visualize the implicated hydrologic trade-offs is of immediate policy relevance.

2. Methods

2.1. Optimization problem and decision variables

We use the notation in (Kasprzyk et al., 2013) to formulate the new GWSA treaty as a multi-objective optimization problem seeking to minimize a vector **F** of P objectives $(f_1, f_2, \ldots, f_P)$ by choosing a vector **l** of decision variables within a decision space Ω:

$$\min_{\mathbf{l}\in\Omega} \quad \mathbf{F}(\mathbf{l}) = (f_1, f_2, \ldots, f_P) \quad \text{s.t.} \quad c_i(\mathbf{l}) \leq 0 \forall i \in [1, q] \tag{1}$$

where $c_i(\mathbf{l}) \leq 0 \forall i \in [1, q]$ represents q constraints on the vector of decision variables. Feasible solutions are defined as those meeting all the imposed constraints. A solution $\mathbf{F}(\mathbf{a})$ dominates another solution $\mathbf{F}(\mathbf{b})$ if $f_i(\mathbf{a}) \succeq f_i(\mathbf{b}) \forall i$ and $\exists j | f_j(\mathbf{a}) \succ f_j(\mathbf{b})$. The solution is Pareto optimal if it is non-dominated with respect to *all* other feasible solutions (Kasprzyk et al., 2013).

We defined decision variables by parameterizing the current treaty under the premise that its structure will serve as a basis for its renewal in 2026. The current treaty allocates a fixed percentage ($p_{Q1} = 50\%$) of incoming streamflow to Bangladesh (and the remaining flow to India), up to a threshold ($Q_2 = 35,000$ cubic feet per second, or cusec) allocated to Bangladesh. This threshold corresponds to a total incoming streamflow of 70,000 cusec (Q_2 / p_{Q1}) upstream of the diversion. Additional flow beyond that threshold is allocated to India (with flow to Bangladesh maintained at $Q_2 = 35,000$ cusec), up to another threshold of 40,000 cusec allocated to India. This latter threshold is determined by the capacity of the canal diverting the flow towards India (Kawser and Samad, 2016), and is unlikely to be altered in a renewed treaty. Under current treaty allocations, this threshold corresponds to a total flow of $Q_2 + 40,000 = 75,000$ cusec upstream of the diversion. The treaty also includes special provisions for the driest period of the year (March 11 to May 10) during which guaranteed flows are allocated to Bangladesh and India in alternating 10-day periods. The current treaty splits this period, centered around April 10, into $n = 6$ intervals of $m = 10$ days, during which a minimum flow of $Q_{int} = 35,000$ cusec is alternately guaranteed to each country [see Penny et al., 2020].Treaty allocation rules and the five parameters that govern them (p_{Q1}, Q_2, Q_{int}, m and n) are summarized in Fig. 2. These five parameters constitute the decision variable vector **l** of the multi-objective optimization.

2.2. Constraints and enumeration of solutions

The five decision variables are bound by a series of constraints (summarized in Table 1) associated with the physical flow diversion infrastructure and historical legacies. Namely, the feeder canal linking the Ganges at Farakka barage with the Hooghly river has a capacity of 40,000 cusec. Assuming that the physical capacity of the canal will not be increased when the treaty is renewed, this sets a hard limit on the flow that can be diverted to India. Accordingly, Q_2 and Q_{int} are capped at 40,000 cusec. In addition, the current treaty prescribes emergency arrangements if the total flow of the Ganges at Farakka falls below 50,000 cusec. We assumed that this clause will carry over to the renewed treaty, and set a lower limit of Q_{int} at $50,000/2 = 25,000$ cusec. This allows each party to benefit from intervals of guaranteed flows before emergency measures are invoked (i.e., for incoming flows at Farakka equal to or higher than 50,000 cusec). Further, the minimum flow for Q_2 is set to

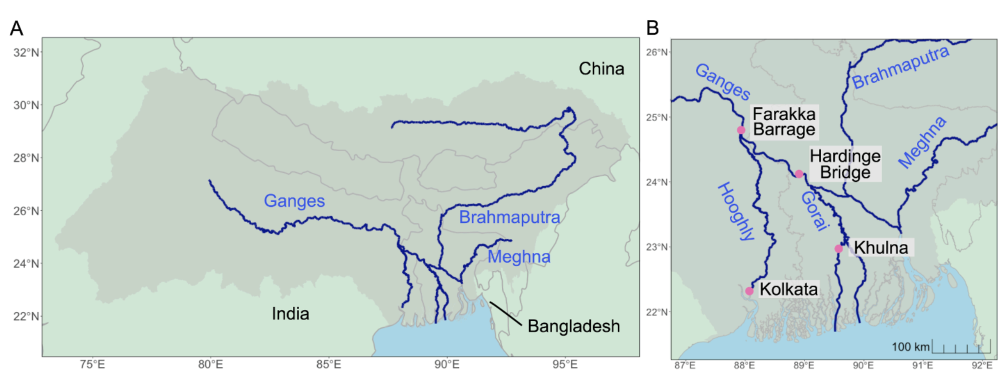

Fig. 1. The Ganges-Brahmaputra–Meghna Rivers (A) and Ganges delta (B).

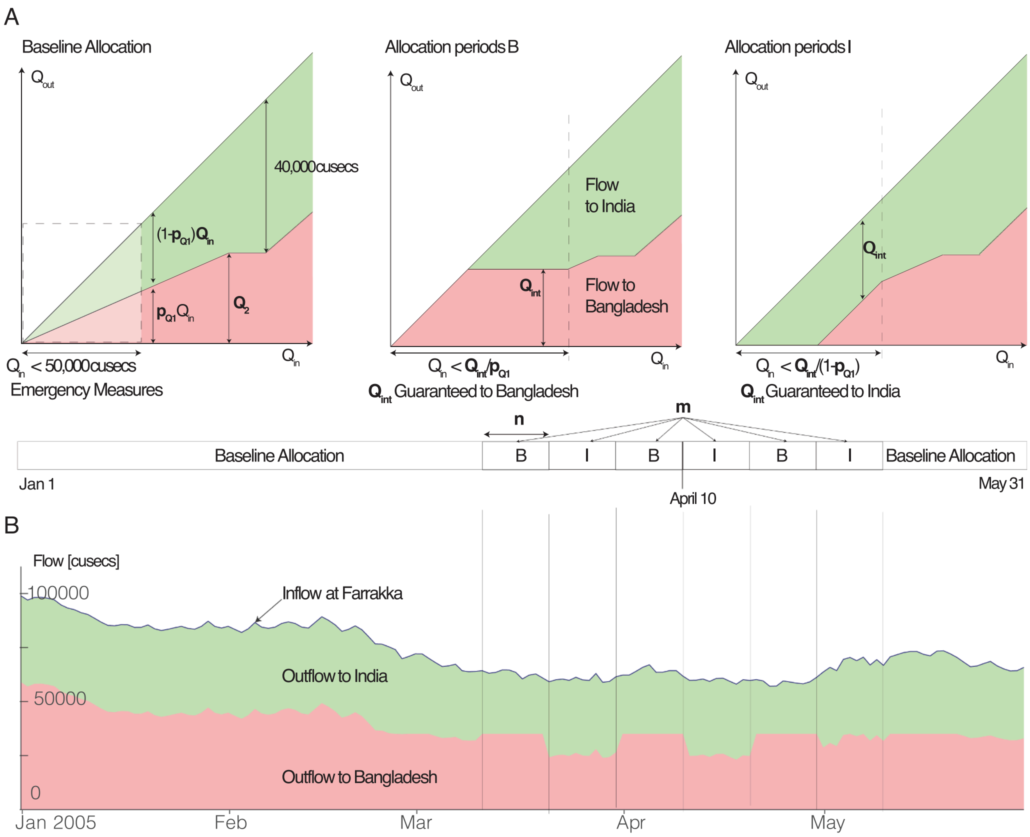

Fig. 2. Flow allocation rules of the current Ganges river treaty. **A.** Streamflow allocations to India (y-axis, green) and Bangladesh (y-axis, pink) as functions of total Ganges flow upstream of the diversion (Q_{in}, x-axis). Sub-panels represent allocation rules outside of intervals periods (left), and during intervals periods with guaranteed flow to Bangladesh ('B',middle) and India ('I', right). Treaty parameters Variables p_{Q1}, Q_2, Q_{int}, n and m are further defined in Table 1. The dashed square on the left panel represents the flow threshold of $Q_{in} = 50,000$ cusec below which emergency provisions are triggered. **B.** Illustration of treaty flow allocations for the 2005 water year.

30,000 cusec, so that there generally remains a period of total flow above emergency measures (50,000 cusec) that is dictated by p_{Q1}. The number and duration of intervals (m and n) are set so that the total period governed by interval allocation remains at or below 150 days, which corresponds to the entire duration of the annual low flow period regulated by the treaty (January 1 to May 31); m must also be an even number for both countries to be attributed identical numbers of guaranteed flow periods. Regarding the percentage of flow allocated to Bangladesh under low flow conditions outside of the interval period, we arbitrarily set its boundaries at 45% and 70%. The current treaty divides these flow conditions equally between the two countries, so deviations from the status quo are likely politically challenging. Yet if the parameter does become altered in the renewed treaty, we assumed it to be more likely in the favor of India due to its favorable hydro-strategic position. The ensuing constraints $c_i(\mathbf{I})$ on the decision variables are summarized in Table 1.

We enumerated 25,121 feasible treaty solutions that span the constrained decision space at regular intervals. These intervals (displayed on Table 1) represent the smallest increment in the decision variables that would be practical to implement. For example, the flow increment of 1000 cusec (or 2.8 m^3/s) corresponds to a height increment of only approximately 15 cm across the 11 gates of 12 m span that form the head regulation structure of the diversion canal (assuming sluice gates with a spillway coefficient of 1). Given these considerations, the intervals in Table 1 are sufficiently small for the enumerated solutions to allow for a reasonable approximation of the true Pareto-optimal set associated with the considered objectives.

2.3. Initial set of candidate objectives

Our initial set of candidate objectives relate to flow conditions in India and Bangladesh immediately downstream of the diversion, and to salinity conditions in the Gorai River in Bangladesh, near the city of Khulna. Flow and salinity conditions in the Gorai are critical in terms of controlling salinity conditions in southwest Bangladesh, a region that is particularly vulnerable and sensitive to saline intrusions from the Bay of Bengal (Mirza and Sarker, 2004). Under the premise that both countries seek to maximize average flows but minimize flow variability and salinity (a strong assumption that is discussed in Section 4.1), we constructed the initial set of 26 candidate objectives described in Table 2 with the aim of capturing the central tendency, variability and extremes

Table 2
Initial set of objective variables.

Flow to India	Flow to Bangladesh	Salinity in Bangladesh
mean[min(Q_I)]	mean[min(Q_B)]	*mean[max(S_B)]
*cv[mean(Q_I)]	*cv[mean(Q_B)]	*mean($S_{B,d}$)
mean(Q_I)	mean(Q_B)	*mean(S_B)
mean($Q_{I,d}$)	mean($Q_{B,d}$)	*cv(mean(S_B))
*days($Q_I < 40k$)	mean[min$_4$(Q_B)]	*max($S_{B,d}$)
mean[min_4(Q_I)]	min(Q_B)	*max(S_B)
min(Q_I)	min($Q_{B,d}$)	*mean[max_4(S_B)]
min($Q_{I,d}$)	min[mean(Q_B]	*days(S_B >5)
min[mean(Q_I)]		*max[mean(S_B)]

Note: Where two statistics are applied, the outermost represents an inter-annual statistic, and the innermost an intra-annual statistic. Subscript I refers to India, B to Bangladesh. Subscript d refers to the period of typically lowest flow (March 11–May 10). Subscript 4 indicates that the considered statistic was determined over a moving window of four years. For example, 'mean[max_4(S_B)]' is the inter-annual mean of the maximum daily salinity for the four years with the highest daily salinity. The number of days throughout the 1998–2017 period that flow to India was under 40,000 cusec is given by the variable 'days($Q_I < 40k$)'. The number of days throughout the twenty year period that salinity in Bangladesh was over 5 ppt is given as 'days(S_B >5)', reflecting an estimate of days in which salinity exceeds suggested levels (Clarke et al., 2015). * indicates variables for which optimization indicates minimization.

of flow and salinity at intra- and inter-annual time scales.

We evaluated the 26 candidate objectives for each of the 25,121 enumerated solutions by applying the corresponding diversion rules to historical (1998–2017) Ganges streamflow upstream of Farakka. This allowed us to simulate historical downstream conditions in India and Bangladesh, had the existing treaty allocations been different. To do so, we proceed as follows (see Fig. 3):

1. Multiple data sources were combined (see Supplementary Information Section S1) to construct estimates of daily inflow to Farakka barrage during the January 1 to May 31 period between 1998 and 2017.
2. Daily streamflow allocations to India and Bangladesh were reconstructed using treaty parameters for each of the 25,121 considered treaty alternatives.
3. A simple physically-based salinity model was used to simulate salinity in the Ganges delta in Bangladesh (Gorai River at Khulna, Fig. 1). The salinity model incorporates advection and first order exchange processes and is influenced by the incoming streamflow, mixing volume (e.g., channel geometry) and downstream salinity conditions; see Section S2 and (Penny et al., 2020).

The resulting simulations of daily streamflow (India and Bangladesh) and salinity (Bangladesh) were then used to compute the statistics corresponding to each candidate objective.

2.4. Dimensionality reduction

Starting with the initial set of candidate objectives, we sought to reduce the number of objectives by exploiting the fact that some objectives might be correlated due to underlying bio-physical relationship. For example, physical constraints (e.g., mass balance, advection and mixing) associate an increased flow to India with a decreased flow and increased salinity in Bangladesh. Characterizing how these dependencies play out between each combination of objectives in Table 2 might allow them to be grouped into clusters that best embody the governing physical trade-offs of the system and discount the effect of potentially redundant objectives.

We used the procedure of agglomerative hierarchical clustering to classify the initial set of candidate objectives according to their similarity across the 25,121 solutions (Legendre and Legendre, 1998). To do so, we defined a dissimilarity (or distance) matrix

$$D_{ij} = \left(1 - R_{ij}\right) \in [0, 2]$$

where R_{ij} is the Pearson correlation coefficient between the simulated value of objectives i and j across the 25,121 enumerated solutions. Prior to calculating the Pearson coefficient, statistics associated with salinity levels and flow variability (which parties seek to minimize) were multiplied by -1. We then implemented complete linkage clustering to group the candidate objectives in increasing order of dissimilarity – the most correlated pairs of candidate objectives were grouped first – and produce a cluster tree, or dendrogram (Fig. 4). Another way to consider the problem is to think of the 26 initial candidate objectives as a network of 26 nodes with distance matrix given by D_{ij}. Hierarchical clustering was used to identify the communities within the obtained graph that best represents its structure (Radicchi et al., 2004).

Clusters of similar candidate objectives were determined by cutting

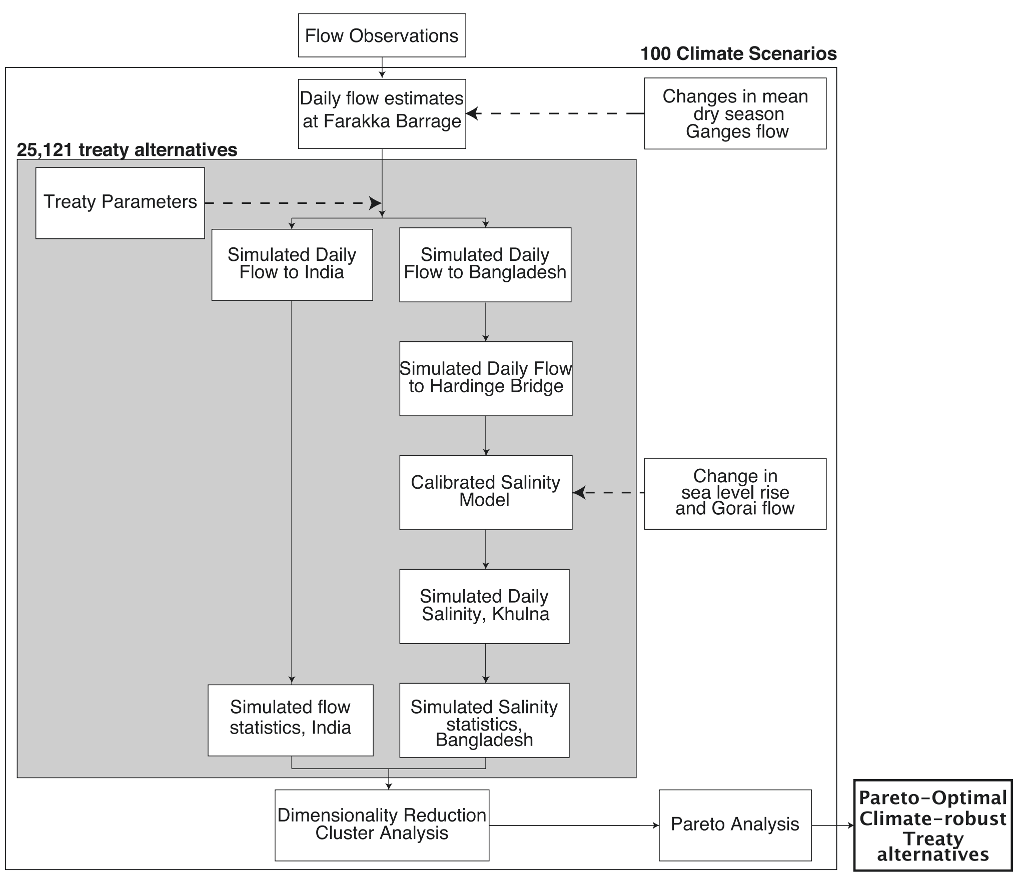

Fig. 3. Approach used to generate treaty solutions (grey) and evaluate their sensitivity to changing climate drivers (white). Procedures associated with the reconstruction of historic streamflow at Farakka and the calibration and validation of the salinity model are presented in Sections S1 and S2 of Supplementary Information.

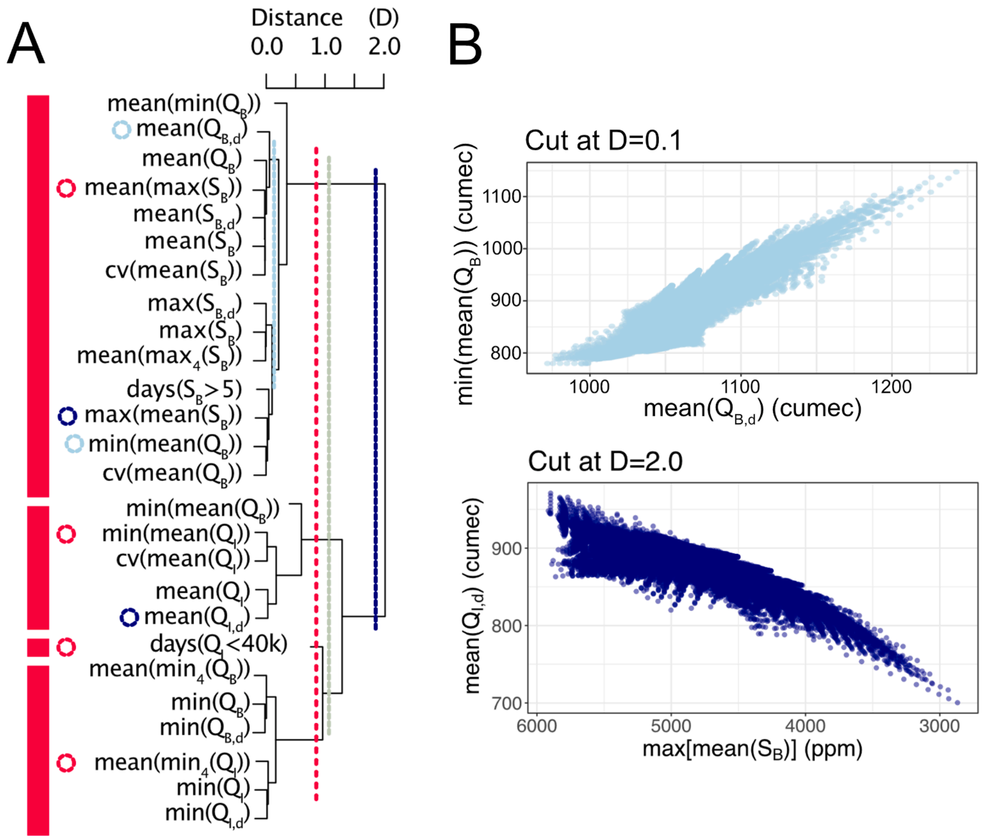

Fig. 4. Hierarchical clustering. The dendrogram of the initial set of 26 candidate objectives was pruned at different distance values D^* (Panel A, colored vertical lines). One objective was randomly selected for each pruned sub-tree (Panel A, colored circles), and used to map the 25,121 treaty alternatives (Panel B) to visualize the associated trade-offs. Pruning the tree at an excessively low value of D^* (light blue) results in a large number of clusters with objectives that are strongly correlated across clusters. In contrast an excessively high value of D^* (dark blue) results in a small number of highly anti-correlated clusters. The former might fail to identify the fundamental trade-offs of the problem; the latter might fail to capture its relevant complexity. The selected cutoff at $D^* = 0.8$ (red) achieves a balance between these two extremes with 4 strongly anti-correlated clusters. Red rectangles on the dendrogram (Panel A) indicate the four clusters considered in the subsequent analyses, and red circles indicate their central objective variable. Corresponding scatterplots of solutions (i.e. treaty alternatives) are provided in Fig.. 5.

the dendrogram so that all candidate objectives contained by a cut branch fall within a single cluster. Although several techniques exist to optimally prune hierarchical dendrograms [e.g., (Langfelder et al., 2008)], a parsimonious approach is to cut the tree at a constant dissimilarity threshold D^*. An optimal value of D^* will maximize both the *similarity* of objectives within clusters and the *dissimilarity* of objectives between clusters. An excessively small D^* would produce a large number of similar clusters and fail to capture the governing trade-offs of the problem. In contrast, an excessively large D^* would group dissimilar objectives within the same cluster. If the objectives within a cluster are too dissimilar, the choice of the particular objective used to represent the cluster in the Pareto optimization will strongly influence its result (Figure S5). Here we used a dissimilarity threshold $D^* = 1$. This corresponds to a Pearson correlation coefficient $R^* = 0$, meaning that objectives within clusters are positively correlated across the 25,121 enumerated solutions, whereas objectives across clusters are negatively correlated. In our specific case study, a threshold $D^* = 1$ falls at the limit between three and four clusters (Fig. 4A, light green line). We opted for four clusters to increase the similarity of objectives within a cluster and make the Pareto optimization less sensitive to the particular choice of the objectives used to represent each cluster.

We identified a single representative objective per cluster by considering the correlation matrix R_{ij} associated with each cluster (one matrix by cluster) as an analog to a graph adjacency matrix, where each node represents an objective. For each matrix, we then identified the 'node' (i.e. objective) with the highest measure of degree centrality (Golbeck, 2015). The approach indicated the following objectives as central to each cluster:

1. mean[max(S_B)], which is the inter-annual mean of the intra-annual maximum of daily salinity in Bangladesh (Gorai River at Khulna)
2. mean[min_4(Q_I)], which is the inter-annual mean of the four lowest intra-annual minimum daily flows to India
3. min[mean(Q_I)], which is the inter-annual minimum of the intra-annual mean flow to India
4. days($Q_I < 40k$), which is the number of days (in the full 1998–2017 period) where flow to India is less than 40,000 cusec, which is the maximum flow that India can receive

Although these four objectives have the highest degree of centrality within each cluster, the chosen threshold $D^* < 1$ ensures that the objectives were positively correlated within clusters. Three of the four objectives pertain to India, but two of these clusters contain variables associated with Bangladesh. For instance, min(mean(Q_I)) and mean (min_4(Q_I)) are highly correlated with min(mean(Q_B)) and mean (min_4(Q_B)), respectively. As a result, the specific variable chosen for each cluster has little effect on the outcome of the Pareto-optimization, as shown in the sensitivity analysis in Section S3.

2.5. Pareto frontier and scenario-neutral analysis

The four central objectives ($Q_I < 40k$), min[mean(Q_I)], mean [min_4(Q_I)], and mean[max(S_B)]) embody the fundamental trade-offs of the biophysical system regulated by the Ganges treaty. The corresponding Pareto frontier – the set of solutions that are Pareto-optimal – can be identified as the convex hull of the enumerated solutions mapped in the four dimensional space spanned by the considered objectives. This mapping for the 25,121 treaty solutions, and the associated Pareto frontier is represented in Fig. 5 and discussed in the Results section (Section 3.1). Under the assumption that neither party will settle for a treaty that is non-dominant under current climate conditions, the Pareto-optimal set contains all treaty solutions that parties might plausibly choose from under the considered set of four central objectives. We further determined which treaty solutions of the Pareto-optimal set are also better than the current treaty according to all four objective variables. These treaty solutions are referred to as POB (Pareto-optimal and

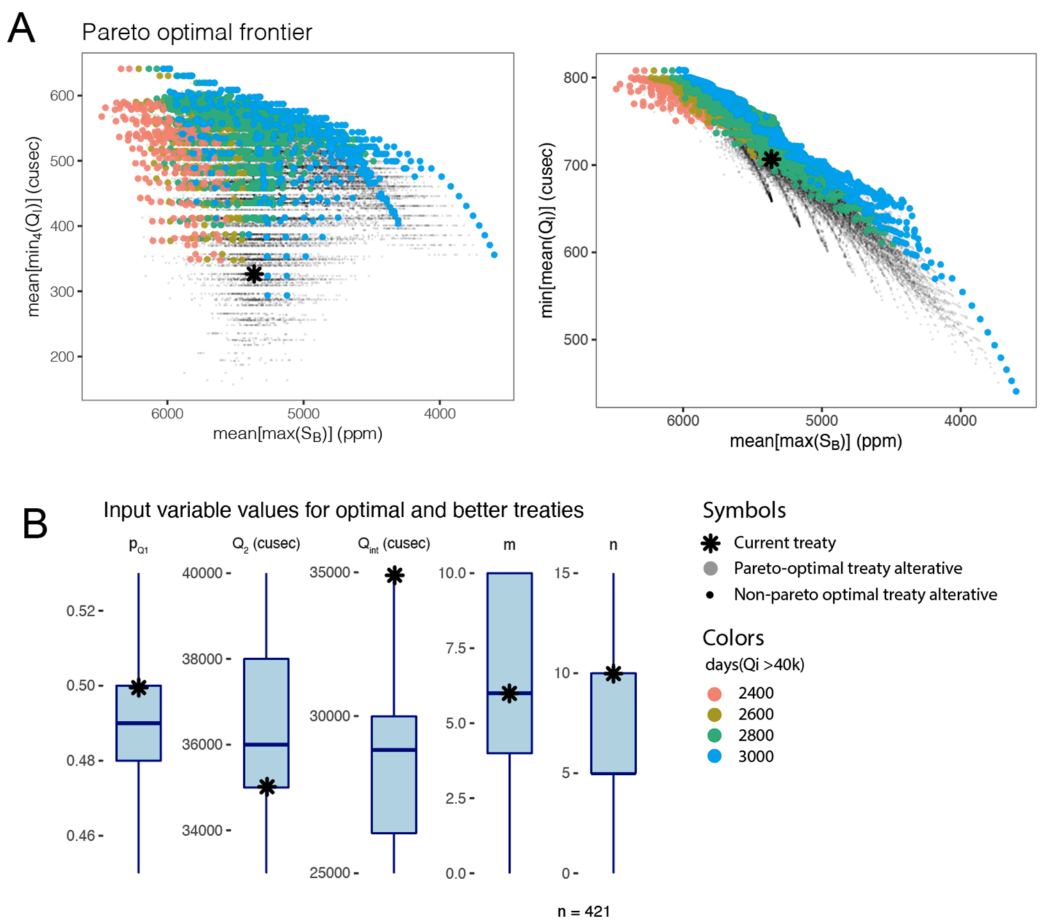

Fig. 5. Pareto analysis results under historic climate conditions. **A.** Enumerated treaty solutions (N = 25,121) are plotted according to the performance measure of the central objective corresponding to each of the four selected clusters (axes and colors). The 2,252 treaty solutions that are on the Pareto frontier (i.e. that are Pareto optimal according to the four considered objectives) are represented as large symbols. The black star indicates the performance measures for the four objectives applied to the current treaty. **B.** Boxplots of allocation parameters associated with the treaty solutions that are Pareto-optimal and better than the current treaty (N = 421), according to the four selected objectives. Parameters corresponding to the current treaty are represented as black stars.

better), under the assumption that parties will not settle for treaty solutions (whether Pareto-optimal or not) that are worse than the status quo with regards to any of the four considered objectives.

To account for the effect of climate change, we identified the subset of solutions that remain in the POB set under the broadest range of plausible climate conditions. We used the scenario neutral climate vulnerability approach described in Brown et al. (2012) to determine which of the treaty solutions that are POB under historical climate conditions would remain so under alternative future climates. The effect of climate change on Ganges streamflow depends on the combined effects of glacial melt in the Himalayas, changing rainfall patterns during the Indian monsoon and changing land and water use in the Gangetic plain, all of which are highly uncertain (Wilby and Dessai, 2010; Pervez and Henebry, 2014; Immerzeel et al., 2010; Lutz et al., 2014). In weighing all scenarios equally, we do not evaluate the *risk* (likelihood × impact) associated with climate change for each treaty allocation. Instead, we provide a first order evaluation of the robustness of treaty alternatives to specific changes in key climate drivers, without having to rely on a fully specified and down-scaled climate model to quantify these changes. In situations where climate predictions are readily available, the approach can be further refined by using weights to represent the predicted probability of each climate scenario (Brown et al., 2012).

In the context of the Ganges, we consider three sources of hydro-climatic changes.

1. Changes in flow available at Farakka barrage might be altered by changing precipitation patterns and water use upstream (Wilby and Dessai, 2010). In particular, precipitation is expected to decrease in critical pre-monsoon months (Pervez and Henebry, 2014), despite an overall expected *increase* of annual precipitation (Pervez and Henebry, 2014; Immerzeel et al., 2010). As a result, streamflow in the upper watershed of the Ganges is expected to increase through 2050 (Lutz et al., 2014) in part due to greater runoff from melting glaciers (Immerzeel et al., 2010; Kumar et al., 2011; Siderius et al., 2013), but the overall streamflow contribution from the Himalayas is expected to decrease with rising temperatures later in the century (Nepal et al., 2014). We incorporated these diverging predictions by simulating changes in the dry season Ganges streamflow (upstream of the Farakka barrage) ranging between −20% and + 20% of their historical value, roughly approximating the range of expected changes in the basin [see (Immerzeel et al., 2010; Kumar et al., 2011)]. We simulated these changes by multiplying daily simulated dry season streamflow into Farakka barrage by a constant factor ranging between 0.8 and 1.2.
2. Sea level rise will affect salinity conditions in the delta. The sea level in the Bay of Bengal is estimated to rise approximately 0.43 – 0.84 m by 2100 (Oppenheimer et al., 2019). We simulated increases in sea level of 0, 0.2, 0.4, 0.6 and 0.8 m. These changes were incorporated into the boundary conditions of the salinity model as described in Section S2 in Supplementary Information.
3. The geomorphology of the delta might be altered due to natural (sediment deposition) and anthropogenic (dredging) alteration. In particular, our salinity model focuses on the Gorai river, which is a major distributary of the Ganges river (see Fig. 1) that supplies freshwater to Southern Bangladesh, a region particularly prone to river salinization. The proportion of the Ganges streamflow diverted towards the Gorai has diminished subtantially over the past few years (Mirza, 1997), but might also increase in a future climate (e.g., if dredging operations are conducted Mohiuddin, 2002). To account for these possibilities, we considered alternative scenarios where the proportion of the Ganges flow diverted towards the Gorai river is assumed to be 80%, 100%, 120% and 160% of the current one. This

change is implemented by multiplying the parameter of the salinity model associated with advection (a in Section S2) by a constant representing the relative change in the Gorai flow diversion.

3. Results

3.1. Pareto-optimal treaty alternatives

We found that approximately 10% (2,252) of the 25,121 enumerated treaty solutions were Pareto-optimal under historical climate conditions, when considering the four selected objectives (Fig. 5A). Without the dimensionality reduction procedure from Section 2.4 (i.e. considering the full set of original objectives), the Pareto-optimal set of solutions would comprise at least 90% (22,566) of all enumerated solutions (see Supplementary Text S4). Remarkably, the current treaty is *not* among the Pareto-optimal treaty solutions, meaning that other treaty solutions would have (weakly) improved on all four objectives under historic conditions. Importantly, the above results are contingent on the four considered objectives. These were determined by our cluster analysis to optimally capture the fundamental trade-offs of the biophysical system, and therefore conditioned by the initial set of candidate objectives that is fed into it, as discussed in Section 4. The current treaty might well be Pareto-optimal under another (to us unknown) set of objectives that were considered when the treaty was established.

Of particular relevance are treaty solutions that are both (i) Pareto optimal and (ii) better than the current treaty with respect to the four considered objectives. These treaties, referred to as 'Pareto-optimal and better' (POB), make up approximately 19% of the Pareto optimal treaty solutions, or 1.7% of the total set of solutions. The distributions of the decision variables of POB treaty solutions are displayed in Fig. 5B. For most decision variables, the corresponding parameter of the current treaty fits within the interquartile range of POB solutions. This suggests that the POB treaty solutions are not substantially different from the current treaty for most decision variables. An exception arises for the parameter representing the guaranteed flow allocation during interval periods (Q_{int}). Most (>99%) POB treaty solutions have a Q_{int} smaller than the $Q_{int} = 35,000$ cusec of the current treaty, with 75% of the POB treaty solutions with a Q_{int} value between 25,000 and 30,000 cusec. Our results therefore suggest that both parties would benefit from smaller guaranteed flows during interval allocation periods, but *not* from suppressing interval flows altogether.

To interpret this result, consider that interval allocation periods are applied during the period of the year when minimum flow conditions are most likely to occur. Maximizing the minimum annual flow was identified among the central objective by the clustering analysis. Because Q_{int} typically accounts for the majority of total flows available during interval periods, minimum flow for one country generally occurs during the mandated allocation period for the other country (Rahman et al., 2019). Under these conditions, a treaty with a lower guaranteed flow Q_{int} would increase flow availability during the non-allocation intervals. Such a treaty would increase the annual minimal flow of both countries and would therefore dominate treaty solutions with a higher guaranteed flow.

3.2. Robustness to changing climate conditions

Fig. 6A describes the climate-sensitivity of Pareto-optimal solutions using two satisficing-based robustness measures (i.e. measures that reflect the tendency of decision makers to seek outcomes that meet one or more requirements but may not achieve optimal performance Herman et al., 2015). The first analysis filters out the treaty solutions that are not POB under historic condition. It then evaluates the proportion of the remaining POB solutions that remain Pareto-approximate for each climate scenario.. Results in Fig. 6A (dashed) suggest that the POB treaty solutions are comparatively more sensitive to changes in mean dry season streamflow than to rises in sea level. Approximately 50% of the 421 treaty solutions that are POB under current climate conditions remain POB for up to 80 cm increases in the mean sea level of the Bay of Bengal. In contrast, only 20% of currently POB treaty solutions remain so if mean dry season streamflow decreases by 20%. The set of POB solutions appears most sensitive to *increases* in mean dry season flows: a 20% increase in dry season streamflow decreases the set of POB treaties

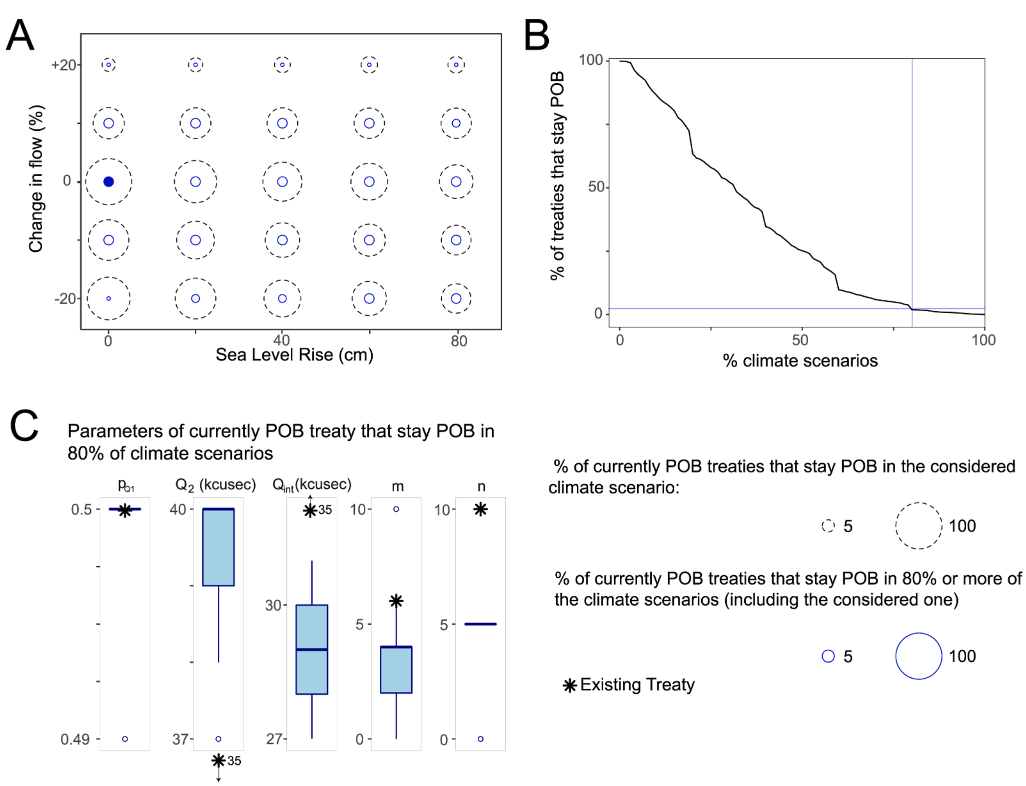

Fig. 6. Robustness of treaty alternatives to changing climate drivers. **A.** Dashed circles represent the proportion of currently Pareto-optimal and better (POB) treaties that will remain POB under changing conditions of sea level (x-axis) and mean dry season streamflow (y-axis). Blue circles represent the proportion of treaty solutions that are also Pareto-optimal or better for 80% of the climate scenarios.The filled blue circle represents the proportion of treaty solutions that are *currently* POB and remain POB for 80% of the scenarios. **B.** Fraction of the currently POB solution set (x-axis) against the fraction of climate scenarios for which they remain POB (y-axis). The fraction of currently POB solutions remain POB in 80% of the considered scenarios is represented in blue vertical line (approximately 4%) and corresponds to the filled blue circle in panel A. **C:** Distributions of decision variables associated with treaty solutions that are POB for at least 80% of climate scenarios (filled blue circle in Panel A). Parameters of the current treaty are represented as a black star.

by 92%. In a second analysis, we determined for each state-of-the-world scenario, the subset of treaty alternatives that are also Pareto-approximate in most (80%) other scenarios (Fig. 6A, blue circles, an approach akin to the domain criterion robustness metric discussed in (Herman et al., 2015). The sets of treaty alternatives that remain POB under each of the three types of changes (sea level rise, increasing dry season flow and decreasing dry season flow) have similarly distributed parameters (Fig. 6C). This suggests that there is substantial overlap between the three sets. As seen in Fig. 6,B 4% of the treaties that are POB under current climate are also POB for 80% or more of the considered climate scenarios. These results are robust to uncertainties associated with geomorphological changes (dredging and silting) in the Gorai distributary, as shown in Figure S4. In describing the proportion of treaties that are POB under a given climate scenario, the first analysis (Fig. 6A dashed) evaluates how climate change might affect the difficulty of the problem. A larger proportion of POB treaties means that the solution that gets ultimately selected has a higher chance of being POB, i.e. the negotiation space is larger. In contrast, the second analysis (Fig. 6A blue) is helpful if there is substantial uncertainty on the likelihood of each scenario. It allows identification of the subset of currently POB treaty solutions that are robust in that they remain Pareto-optimal in most scenarios. Lastly we should note that both analyses pre-filter to keep only solutions that are currently Pareto optimal, under the assumptions that parties will not select a solution that is not currently Pareto-optimal. While intuitive, this assumption can be disputed as it is possible that a party prefers a solution that might be Pareto-optimal in the future, even if it is not Pareto optimal today.

We turn our attention to the decision variable values associated with robust POB solutions. Climate-robust treaties are a subset of the treaty solutions that are POB under current climate conditions and so, unsurprisingly, have similar distributions of decision variables (Fig. 6C). In particular, their interval flow threshold Q_{int} is generally smaller than that of the current treaty in order to navigate the trade-off between average and minimum dry season flows (see previous Section). However, climate-robust treaties differ from the wider set of POB treaties in that they have fewer and shorter intervals (smaller n and m) and a significantly larger Q_2 threshold than the current treaty. To interpret these results, consider that a shorter period regulated by interval flows allows for a larger portion of the dry season to be governed by proportional flow allocation. We speculate that this, in turn, might decrease the total number of days with flow allocations less than 40,000 cusec, which was identified as a central objective by the clustering analysis. However, a shorter period with guaranteed interval flows might also decrease the treaty's ability to dampen salinity conditions through increased freshwater flow. Indeed, maximum salinity conditions generally occur towards the end of May (a few weeks *after* minimum flow conditions), during a period no longer regulated by interval flows. Under these conditions, we speculate that increasing Q_2 is Pareto-improving because it increases the flow available to Bangladesh to mitigate river salinity during this critical period. We note that these results are likely driven by the fact that salinity conditions in India would likely be affected by an increase in Q_2 but were *not* included in the initial set of candidate objectives variables due to unavailable data, as discussed in Section 4.

4. Discussion

The optimization of shared river water is a complex challenge that requires reconciling the multiple objectives of numerous stakeholders, at times within a complex and not necessarily cooperative negotiation process. Problem-framing uncertainty can then emerge from the fact that stakeholder preference might be kept private for strategic reasons, causing the true vector of combined stakeholder objective to be hidden. This uncertainty adds on to uncertainties about future states of the world associated with climate change. The exploratory modelling approach that we propose combines hierarchical clustering with scenario neutral analysis to mitigate both types of uncertainties and facilitate the discovery of robust (Pareto) optimal river treaty configuration. It relies on a series of important assumptions, namely (i) an initial set of candidate objectives must be appropriately enumerated, (ii) these objectives must be clustered in a way that does not lose (too much) information about Pareto dominance, (iii) the Pareto optimal set of solutions must be accurately estimated, (iv) Pareto dominance must be an effective filter (i.e. the ideal solution must indeed lie within the estimated Pareto-optimal set) and (v) future states of the world must be properly enumerated. These five assumptions are individually discussed in the following paragraphs.

4.1. *Initial set of candidate objectives*

Whether the approach designates a treaty as Pareto-optimal is ultimately dependant upon the initial set of objective variables that are fed into the clustering algorithm. The 26 streamflow and salinity statistics chosen in our illustrative example were based on data availability and intuitive assumptions on the broad objectives of each party: maximizing streamflow, and minimizing salinity. In particular, we did not have access to calibrated models of salinity and siltation on the Indian side, both of which were stated as minimization objectives by India in their use of the Ganges water (Salman and Uprety, 1999). Including these variables into the initial set of objectives might have led to a different set of POB treaties. More fundamentally, by focusing on a specific set of state-based statistics, the approach does not engage with broader classes of objectives beyond statistics of flow and salinity (e.g., economic, equity, risk mitigation and sectoral priorities) that might be important to policy-makers in real transboundary river systems.

These considerations have two important implications for the practical applicability of our approach. First, the approach relies on appropriate biophysical models that are able to accurately simulate all considered objective variables. The development and calibration of these models may require effective data-sharing and joint research effort between the countries party to the agreement. Second, the approach should be integrated within a broader process of knowledge co-production that acknowledges preexisting power dynamics and historical legacies amongst stakeholders, in both the scientific and policy realms [see Wyborn et al., 2019]. This context should inform the formulation of the initial set of objective variables and the interpretation of the resulting Pareto partition.

4.2. *Clustering and information loss*

Reducing the dimensionality of the objective set implies a tension between simplifying the optimization problem and losing important information. This tradeoff is governed by the cutoff distance D^* which determines the minimum level of correlation between the objectives within the clusters (and therefore the number of clusters and the extent of information loss). While some information loss is inevitable, it should minimally impact the composition of the ensuing Pareto-optimal set. The numerical experiment described in Supplementary Text S3 assesses the relationship between the size of the objective set and the relative ordering of objective rankings. We evaluated how sensitive the composition of the Pareto optimal set is to the two arbitrary parameters of the clustering approach, namely the choice of cutoff distance D^* and the choice of the 'central' objective to consider for each cluster. We found that the composition of the Pareto-optimal set was robust to both choices, as long as the objective chosen to represent each cluster has a sufficient degree of centrality within the cluster.

4.3. *Accuracy of approximated Pareto-optimal set*

Errors on the Pareto-optimal set can emerge from an incomplete enumeration of treaty solutions. As argued in Section 2.2., the bounds on the five decision variables represent physical constraints related to diversion infrastructure or known historic legacies. Similarly, the enumeration intervals represent the smallest increment in the decision variables that would be practical to implement. Based on these considerations, we believe that the enumerated solutions are an accurate representation of the true set of solutions within the considered decision space. However, a more fundamental assumption concerns the decision space itself and its five decision variables which are based on the current treaty. The structure of the current treaty is rooted in a long history of bilateral interactions between India and Bangladesh over the Ganges river, which makes it likely to be carried over to the renewed treaty in 2026. For example, the 10-day intervals with alternating flow guarantees date back to an initial agreement that was finalized days before the commission of the Farakka barrage (Salman and Uprety, 1999). The initial agreement was signed on April 18, 1975 and regulated withdrawals by India in portions of 10 days during the 41 remaining days of that single year's dry season. However, the 10-day intervals of the current treaty have been criticized as propitious to unilateral flow withdrawals (Thomas, 2017) and as causing severe water scarcity during the intervals with non-guaranteed flow (Rahman et al., 2019). These considerations point to the potential for also examining treaty solutions that do not conform with the current treaty structure. For example, simulations by Kilgour and Dinar (2001) found that a flexible allocation based on flow forecasts might increase total welfare by up to 10% in dry years.

4.4. Overlap with true set of Pareto-optimal solutions

Our approach mitigates strategic framing uncertainty by identifying governing set of objectives based on (known) physical constraints of the systems, rather than the (hidden) preferences of its stakeholders. It follows that the ensuing set of objectives unlikely corresponds to the 'true' vector of combined stakeholder objectives, which remains hidden. Rather, the dimensionality reduction approach can be seen as a way to simplify a poorly framed (due to hidden objectives) many-objective optimization problem, using information available to *all* stakeholders. Because of this (and assuming all above assumptions hold), we conjecture that the ensuing set of Pareto-optimal solutions contains the true set of Pareto-optimal solutions. However, without knowledge of the true set of stakeholder objectives, this conjecture is challenging to test. At the very least, the hierarchical clustering approach that we propose (particularly the dendrogram in Fig. 4) can be used as a tool to help stakeholders visualize the governing trade-offs of the considered biophysical system.

4.5. Future states of the world and non-stationary climate

International river agreements are traditionally based on long-term flow statistics computed from historic observation [e.g., Rahman et al., 2019]. The underlying assumption of a stationary flow regime is unlikely to hold in the context of climate change. The scenario-neutral approach that we propose is a first step towards addressing this issue by evaluating the sensitivity of treaty solutions to changes in key climate drivers, without requiring detailed climate simulations. However, it does not address many of the issues associated with changing flow regimes in transboundary basins. For example, scenario-neutral analyses make implicit assumptions about the range and independence of the climate drivers that can render the ensuing visualization misleading (Quinn et al., 2020). Changes in climate drivers can be correlated and systems might be particularly vulnerable to conditions outside the range of historical events (Borgomeo et al., 2015). As Quinn et al. (2020) put it:

> These assumptions could influence which factors are found to be most important and which policies are most robust, belying their neutrality; assuming uniformity and independence could have decision-relevant implications.

More broadly, using long-term statistics in a non stationary context means that what is being optimized is a hypothetical value that does not exist, i.e. a long term average that may change more rapidly than the underlying timeseries it is theoretically calculated on. While adapted for situations where detailed climate predictions are unavailable, the scenario-neutral analysis can be seen as a temporary patch in the sense that it evaluates the climate sensitivity of a decision that is nonetheless made under the fundamental assumption of climate stationarity.

5. Conclusions

Transboundary water treaties face a variety of challenges due to changing climatic and environmental conditions, raising the issue of how to appropriately update existing treaties for an uncertain future.

We develop an approach that addresses three key questions about transboundary treaty design: i) how to identify governing trade-offs associated with the bio-physical nature of the system; ii) how to visualize and determine the effects of the negotiated parameters of the treaty (decision variables) on its outcomes (objectives); and iii) how to identify agreeable (Pareto-optimal) treaty solution in a way that accounts for a changing and uncertain climate. The approach combines hierarchical clustering with a scenario-neutral analysis to achieve address these questions.

Applied to the Ganges water agreement as an illustrative example, the approach shows promise in its ability to discard sub-optimal treaty alternatives. However, the example also shows that the output of the approach (i.e., the set of identified POB treaties) depends on the initial sets of treaty parameters and objective variables that are fed into the approach. Consequently, the location-specific numerical results that we present are not intended to serve as a basis to renew the treaty. Instead, the approach (rather than the illustrative results that we present) can be applied to support decisions in the much richer informational environment available to actual decision makers. Our illustrative case study is intended to demonstrate the potential for this data-driven approach to support, rather than replace, a broader negotiation process and serve as a shared information basis around which stakeholders can coalesce.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marc F. Muller reports financial support was provided by National Science Foundation.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.jhydrol.2022.128004.

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