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Special Section:
Multi-Sector Dynamics: Advancing Complex Adaptive Human-Earth Systems Science in a World of Interconnected Risks

How Should Diverse Stakeholder Interests Shape Evaluations of Complex Water Resources Systems Robustness When Confronting Deeply Uncertain Changes?

Sai Veena Sunkara[1], Riddhi Singh[2,3], David Gold[4], Patrick Reed[4], and Ajay Bhave[5]

[1]Civil and Environmental Engineering, University of California Davis, Davis, CA, USA, [2]Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India, [3]Interdisciplinary Programme in Climate Studies, Indian Institute of Technology Bombay, Mumbai, India, [4]School of Civil and Environmental Engineering, Cornell University, Ithaca, NY, USA, [5]School of Earth and Environment, University of Leeds, Leeds, UK

Key Points:

- Multi actor and sector robustness trade-offs are often not explored due to narrowly defined robustness metrics
- Robustness rankings for decision alternatives across robustness metrics shed light on trade-offs across actors, sectors, and risk attitudes
- Clarify donor-recipient conflicts between ecological needs and socio-economic development for a proposed water transfer mega-project

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. V. Sunkara,
svsunkara@ucdavis.edu

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Abstract

Robustness analysis can support the design and operation of large-scale water infrastructure projects confronting deeply uncertain futures. However, diverse actors, contextual specificities, sectoral interests, and risk attitudes make it difficult to identify an appropriate robustness metric to rank decision alternatives under deep uncertainty. Here, we clarify how methodological choices affect robustness evaluation using the multi-actor, multi-sector Inchampalli-Nagarjuna Sagar water transfer megaproject in Southern India. We compare a suite of water transfer strategies discovered using evolutionary multi-objective direct policy search (EMODPS), a strategy proposed by regional authorities and the status quo of no water transfer. We stress-test these strategies across scenarios that capture climatic and socioeconomic uncertainties and rank them using robustness metrics representing sectoral perspectives and priorities of different actors with varying risk attitudes. Results show a considerable impact of metric choices on robustness rankings of strategies, with compromise solution discovered via EMODPS as robust. The no-transfer strategy results in the worst water supply robustness with an average volumetric deficit of 17% of total historical demands but emerges as a robust alternative for 6 out of 12 combinations of actor-sectors with high risk aversion. Also, changes in the amplitude of the Indian Summer Monsoon is identified as the most important uncertain factor determining the failure of strategies. Our findings highlight that the selection of robust solutions should be guided by an understanding of how assumed risk attitudes shape stakeholders' perceptions of vulnerabilities. These findings are generalizable to large infrastructure projects with diverse stakeholders and multisectoral impacts.

Plain Language Summary

Climate change and growing multi-sectoral competition for water resources are motivating the design and evaluation of infrastructure-based adaptation actions. Here, we explore the Inchampalli-Nagarjuna Sagar (INS) mega water transfer project; a multi-actor and a multi-sector project that aims to transfer water from the Godavari basin to the Krishna basin in Southern India. The project will affect multiple sectors including agriculture, domestic water supply, and downstream aquatic ecology of both rivers and involves multiple actors—the donor, recipient basin and the combined system. It is critical to understand if the INS mega water transfer can robustly meet its intended benefits while limiting unintended consequences in the future. We formally explore different combinations of actors and sectors' objectives, their risk attitudes, and scenario sampling strategies providing a rich context for understanding conflicts and limiting the unintended consequences of myopic analyses. Results show emergent tradeoffs between the ecological requirements of the donor and the water supply needs of the recipient. Our analysis indicates that large-scale water infrastructure projects need to employ broad exploratory robustness analyses that better engage with conflicting stakeholder objectives and that help to clarify how differences in risk aversion shape the vulnerabilities of preferred actions.

1. Introduction

Water resources in many parts of the world face growing hydroclimatic and socio-economic pressures (Bijl et al., 2018; Kummu et al., 2010; Mekonnen & Hoekstra, 2016). Globally, water scarcity is projected to increase due to climate change impacts on mean temperature and precipitation variability, as well as increasingly extreme floods and droughts (Greve et al., 2018; Masson-Delmotte et al., 2021). The economic consequences of water scarcity are highly uncertain and sensitive to regions' capacities to adapt to these deeply uncertain hydro-climatic changes (Dolan et al., 2021). Deep uncertainty refers to conditions where parties to a decision lack a consensus on the likelihoods and/or distributional forms of key system inputs (Knight, 1921; Lempert, 2002; Lempert et al., 2006; Marchau et al., 2019). Large scale water infrastructure projects have a critical role in addressing these challenges (Bhaduri et al., 2008; Gohari et al., 2013; Grigg, 2019). Among them, inter-basin water transfer (IBWTs) megaprojects with investments of approximately $2.7 trillion form a major global focus and pose severely challenging decision contexts (Shumilova et al., 2018).

IBWTs must balance irrigation needs, domestic water supply, hydro-electricity generation, and other uses across multiple participating river basins, requiring their design evaluation to consider the diverse interests of a broad array of sectors. Some IBWTs have been criticized for their ecological consequences and over-exploitation of donor basin's water resources, indicating that traditional evaluations are perhaps myopic about the long-term impacts on the impacted stakeholders (Gohari et al., 2013; Wu et al., 2020; Zhuang, 2016). These multi-decadal megaprojects require an understanding of the dynamic co-evolution of the coupled human-natural systems in which they are placed, especially in key drivers of climate and demands. Projections of these drivers are often deeply uncertain, challenging the traditional use of aggregated cost-benefit analysis to discover transfer policies. At the local scale, future runoff changes are deeply uncertain due to uncertainties associated with projections of potential future temperature and precipitation changes (Bhave et al., 2018; Douville et al., 2021; Schewe et al., 2014). Concurrent changes in socio-economic conditions are also deeply uncertain, as they are a consequence of a multitude of factors pertaining to the coupled human-natural system, changes in water demand priorities, and changing policy landscapes (Moallemi, Kwakkel, et al., 2020; Quinn et al., 2018). Deep uncertainty compounds existing challenges to traditional design approaches for IBWTs. For example, a recent ex post evaluation of traditional design approaches for IBWTs have shown that they often systematically underestimate water scarcity in the donor basin and overestimate the demands within the recipient basin (Huang et al., 2021).

Exploratory modeling-based frameworks such as Robust Decision Making, Many-Objective Robust Decision Making (MORDM), Information Gap theory and Decision Scaling seek to discover *robust* alternatives that perform well across a range of deeply uncertain futures (Ben-Haim, 2006; Brown et al., 2012; Gold et al., 2019; Hadjimichael et al., 2020; Kwakkel & Haasnoot, 2019; Lamontagne et al., 2018; Moallemi, Zare, et al., 2020; Moallemi et al., 2021; Singh, 2023). Robustness evaluation of IBWTs requires the analyst to decide how to represent the multiple stakeholders involved. Although challenging, robustness definition(s) should be identified through co-production of knowledge that includes all relevant stakeholders (Bhave et al., 2022; Eriksen et al., 2021; Moallemi, Zare, et al., 2020; Wyborn et al., 2019). This would be best achieved by stakeholder workshops, an iterative process that results in co-production of knowledge (Voinov et al., 2018). This remains highly challenging for large-scale infrastructure projects as by their very nature, they involve multiple actors spread across spatio-temporal and socio-economic gradients. There may also be socio-political limitations in engaging a diverse group of stakeholders due to differences in ideologies and varying degrees of understanding of the decision process (Eriksen et al., 2021).

The emerging field of Decision Making Under Deep Uncertainty (DMDU) provides a starting point to frame robustness definitions for the design and evaluation of IBWTs (Marchau et al., 2019). Recent literature highlights a rapid proliferation of robustness metrics and their impact on the preferential rank ordering of proposed alternative designs and/or operational strategies (Bartholomew & Kwakkel, 2020; Borgomeo et al., 2018; Herman et al., 2015; Kwakkel, Eker, & Pruyt, 2016; McPhail et al., 2018). There have been an increasing number of applications of decision-making under deep uncertainty approaches globally (see Marchau et al., 2019). Kaatz (2015) reviews several applications of robust decision-making methods in planning water systems. A specific example is the Colorado River; where MOEAs and MORDM methods have been utilized in decision-making (Smith et al., 2019, 2022). Deep uncertainty is assessed and used for climate adaptation planning in New Zealand (Lawrence et al., 2018). Other major examples include the development of the Louisiana Coastal Master Plan (Fischbach et al., 2012), delta management in the Netherlands (Bloemen et al., 2019), and the Colorado Water Conservation Board's efforts to manage vulnerabilities to drought (Hadjimichael et al., 2020). These examples show the potential of using the methods related to planning under deep uncertainties (DU) in the real world. In the Indian context, IBWTs have been assessed using historically observed streamflows and assumed future demand scenarios. Thus, so far stochastic uncertainty or deeply uncertain factors have not been explicitly considered in the planning of these projects (NWDA, 2021). Therefore, there is a necessity to assess these projects performance under uncertainties associated with climatic and socioeconomic changes during their lifetime of multiple decades. In addition, understanding how the value of the project varies across different actors/sectors and their risk attitudes would provide information for future dialogs between the participating basins.

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In general, robustness quantification requires the specification of methods for generating deeply uncertain futures and aggregating evaluations of strategy performance across these futures (Herman et al., 2015; McPhail et al., 2021). Generating deeply uncertain futures requires an understanding and careful exploration of important system drivers as well as their feasible ranges and plausible statistical properties (McPhail et al., 2020; Quinn et al., 2018, 2020). The aggregate rank evaluations of robustness require an explicit consideration of risk attitudes. Aggregation of robustness performance across sampled scenarios for the future can be based on expected value analysis (Wald, 1950); higher-order moments (Kwakkel, Haasnoot, & Walker, 2016); regret (Savage, 1951) or satisficing criteria (Simon, 1956). Building on the general framework proposed by Herman et al. (2015), McPhail et al. (2018, 2020) show that several underlying methodological choices tacit to measuring robustness can substantially influence robustness-based rankings of decision alternatives. For example, performance aggregation across scenarios embeds assumptions regarding levels of risk aversion of stakeholders. Measuring robustness using traditional expected value focused metrics tacitly assumes risk neutrality, while minimax or worst-case performance across scenarios represents high levels of risk aversion. Thus, robustness criteria require a careful elicitation of requirements (or performance acceptability limits) from stakeholders (Herman et al., 2015; Kwakkel, Eker, & Pruyt, 2016).

In this study, we propose a framework to address the principal challenge of capturing diverse stakeholder views in robustness assessments for large multi-actor infrastructure projects, a central concern when seeking to support co-production processes. Our framework contextualizes how exploratory analysis of multiple robustness metrics can better contextualize the implications of a broad range candidate robustness framings in capturing diverse stakeholder preferences and shaping performance evaluations. Our proposed exploratory robustness assessment provides a mechanism for formally broadening dialog and the inclusion of diverse and potentially under-represented stakeholders. We apply this framework to the proposed Inchampalli-Nagarjuna Sagar (INS) IBWT in Southern India, which aims to transfer water from the Godavari (donor) to the Krishna (recipient) river basin with significant implications for millions of farmers as well as the pharmaceutical and software hub of Hyderabad, India. We extensively assess potential impacts on the participating basins and their water related sectors considering deeply uncertain changes in precipitation patterns and river flows due to uncertain potential future changes in Indian Summer Monsoon and anthropogenic water demands.

2. The Decision Context of the INS IBWT Megaproject

India faces a daunting challenge of ensuring water, food and energy security in a changing climate and rapidly evolving socio-economic conditions. India's National River Linking Project (NRLP) aims to improve water and food security via expansion of irrigated area by ≈350,000 km^2 using 30 water transfer projects totaling in length of ≈14,900 km and a network of 3,000 storage structures (Bagla, 2014; Joshi, 2013). If implemented fully, the NRLP will incur massive water infrastructure investment of >$2 trillion, greater than 60% of the Indian economy of $3.17 trillion. Within NRLP, the INS IBWT proposes to transfer water from the Godavari (donor) to the Krishna (recipient) basin, the two largest river basins of Southern India (Figure 1). The INS IBWT by itself has been justified due to a growing disparity between demand and supply between its participating basins. With a proposed 16,000 Mm^3 annual water transfer over 299 km classified the INS IBWT as a megaproject (NWDA, 2021; Shumilova et al., 2018; Veena et al., 2021). The water transfer is a major socio-economic development intervention for the Nagarjuna Sagar reservoir, which is stressed due to increasing agricultural and urban (primarily Hyderabad city) water demand, as well as demands from another regional political capital, Vijayawada. The INS IBWT is also going to impact the aquatic ecosystems downstream of the donor and local tribal populations that rely on the maintenance of minimum environmental flows (MEF).

Given the high stakes, deep uncertainty, and multi-stakeholder context, the INS IBWT requires a comprehensive evaluation to avoid potential decision lock-ins (Moallemi, Zare, et al., 2020). Average Godavari annual inflows at Perur gage station (77,017 Mm^3) are more than double those at Nagarjuna Sagar on the river Krishna (29,625 Mm^3) (Figure 1b), while their respective command area water demands are ≈603 and ≈8,535 Mm^3(Figure 1c) (Veena et al., 2021). Mean annual precipitation (temperature) is projected to increase by 20%–50% (1°–5°C) in both basins by the end of century (Mishra & Lilhare, 2016), but future water availability and demand dynamics will evolve in complex ways with changes in population as well as the efficiency of the multisectoral water dependent systems that evolve to meet the concomitant increasing human demands (Singh & Kumar, 2019), leading to deep uncertainty.

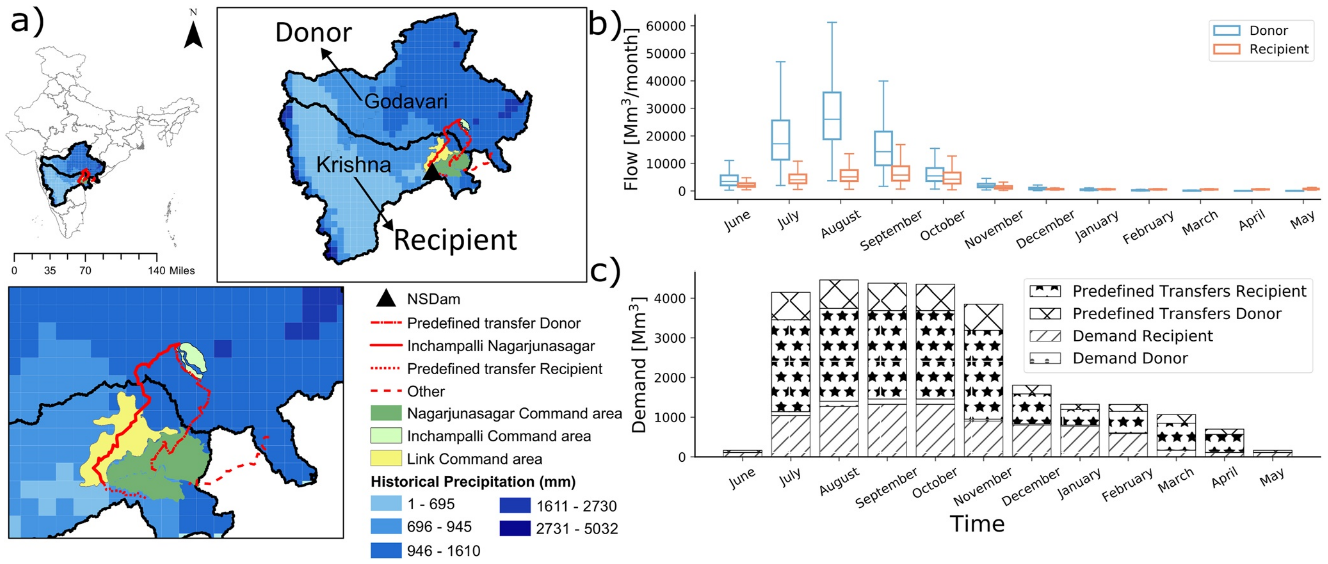

Figure 1. (a) Location of the Inchampalli-Nagarjunsagar (INS) water transfer project connecting the donor (Godavari) and recipient (Krishna) basins. The irrigated command areas for each basin is represented by shades of green and yellow for the link command area. The predefined transfer (PT) from donor and recipient basins are also shown by dot-dashed and dashed line respectively. Historical observed precipitation in the basins is shown in shades of blue (b) Monthly stochastic inflows in donor basin (blue) and recipient basin (orange). (c) Monthly demands and PT for both basins.

In this study, we employ the systems model and cooperative adaptive strategies contributed by Veena et al. (2021). Their original analysis focused on the stationary historical uncertainties affecting Godavari and Krishna inflows, exploiting a water balance model to track reservoir related fluxes, and assessed water transfer strategies against different priorities for environmental flows, domestic water supply and irrigation (please see Veena et al. (2021) for further details). The study formulated cooperative state-aware water transfer strategies where water transfers are decided based on the storage states of both the donor and the recipient reservoirs. Both the donor and the recipient reservoirs are also committed to transfer water to other reservoirs, which impose additional demands on the INS IBWT. These transfers are termed as "predefined transfers" (PT). In this study, we further evaluate the cooperative adaptive INS IBWT operational strategies under deeply uncertain futures and contribute an exploratory framework to guide assessments of their robustness.

Large scale water infrastructure projects such as the INS IBWT involve a number of actors and sectors, each with their own preferences and risk attitudes. Thus, multiple world views are invariably involved in its decision context. Prior literature has explored the consequences of multiple world views using multiple problem framings (Kasprzyk et al., 2013; Lempert & Turner, 2021; Quinn et al., 2017; Singh et al., 2015). Here, we propose a framework to support diverse stakeholders in exploring how they may define the robustness of an operational strategy. This framework can be used for deliberative analysis of candidate stakeholder preferences and/or as an exploratory modeling strategy for discovering the conflicts between stakeholders. The main actors involved in the INS IBWT are the donor (Godavari) basin, the recipient (Krishna) basin, and other basins dependent on water transfers from either of these (i.e., PT). We also define a baseline system level actor that captures a risk neutral rational social planner acting on the expected value of performance objectives averaged over donor and recipient outcomes, following a standard assumption in simulation-optimization literature (Giuliani & Castelletti, 2016; Loucks & Van Beek, 2017; McPhail et al., 2018). Similarly, requirements of all other basins that depend upon the donor (Godavari) and recipient (Krishna) are represented by a system level PT actor.

The different sectors impacted by the INS IBWT are domestic, industrial, agricultural, and ecological. Domestic, industrial and agricultural sectors together constitute the water supply sector. Ecology is affected in two ways. First, MEF downstream of both reservoirs are dependent upon the transfer and reservoir operation rules. MEF has direct consequence on tribal communities downstream of the donor (Godavari) basin that depend upon fishing, thus it is also included here to represent the interests of the marginalized communities (Eriksen et al., 2021). Second, the volume of water transferred (transferred volume, TV) is also considered as a proxy of ecological impact. The lower the amount of water transferred, the lower the potential ecological impact of mixing waters

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Table 1
Multiple Actor-Sector Combinations Explored for the Inchampalli-Nagarjuna Sagar Inter-Basin Water Transfer

	Actor				Sector		
Combination of actor-sector	Donor	Recipient	System	PT system	Water supply	Ecology-TV	Ecology-MEF
1	X				X		
2		X			X		
3	X						X
4		X					X
5			X		X		
6			X				X
7				X	X		
8	X	X			X		
9	X	X					X
10			X			X	
11			X		X	X	
12	X	X	X	X	X	X	X

Note. In each row, the X's identify which actor-sector combinations are used in robustness calculations. PT, predefined transfers for other reservoirs; TV, transfer volume; MEF, minimum environmental flows.

of diverse quality and aquatic compositions. Using this rationale, we constructed two ecology related sectors: ecology-TV, and ecology-MEF. Thus, we envisage 12 actor-sector combinations that may emerge in the decision context of the INS IBWT (Table 1). The performance requirements for these are quantified using definitions discussed in the methods section below.

2.1. Data Sources

The inflow data to the Inchampalli reservoir (donor basin) obtained from Central Water Commission for the time period 1967–2012 is measured at the Perur gauge station. Whereas, inflow to the Nagarjuna Sagar Dam (recipient basin) is obtained from the irrigation and computer-aided design (CAD) department of Telangana, India for the period 1967–2012. This historical inflow data is used for generating multiple realizations of synthetic inflows. The process of stochastic generation of flows is added in the Text S2 in Supporting Information S1. Future projections were created using stochastic generation and deep uncertain factors; the procedure explained in Section 3.2.

3. Methodology

Our main contribution is a formal exploratory modeling framework for better understanding and transparently mapping the consequences of diverse actor and sector preferences as well as risk attitudes when defining robustness metrics within the MORDM framework (highlighted boxes in Figure 2). As is typical for the MORDM framework (Kasprzyk et al., 2013), our exploration of the INS IBWT begins with the identification of the decision context, alternative candidate problem formulations, and generation of alternatives using many-objective optimization considering historical well-characterized uncertainties (WCU) (Section 3.1). In Step I, the term WCU refers to stochastically generated hydroclimatic scenarios that provide a more careful stationary statistical characterization of the internal variability of streamflows and potential drought extremes beyond the limits of the available observation record. Deeply uncertain factors that shape the performance of the alternative operational designs of the transfer are then identified and sampled in Step II (Section 3.2). We then explore tradeoffs across potential combinations of stakeholder preferences across multiple actors and sectors involved in or affected by the decision process (Section 3.3). These preference combinations together with risk attitude specification are used to re-evaluate the Pareto approximate operational transfer design strategies from Step I across scenarios identified in Step II (Section 3.4). In addition to evaluating robustness under DU, we also analyze robustness under the internal hydroclimatic variability in the stochastic WCU baseline. The multivariate robustness estimates thus obtained are further analyzed to identify key actor/sector tradeoffs with a specific focus on the stability of alternatives ranking

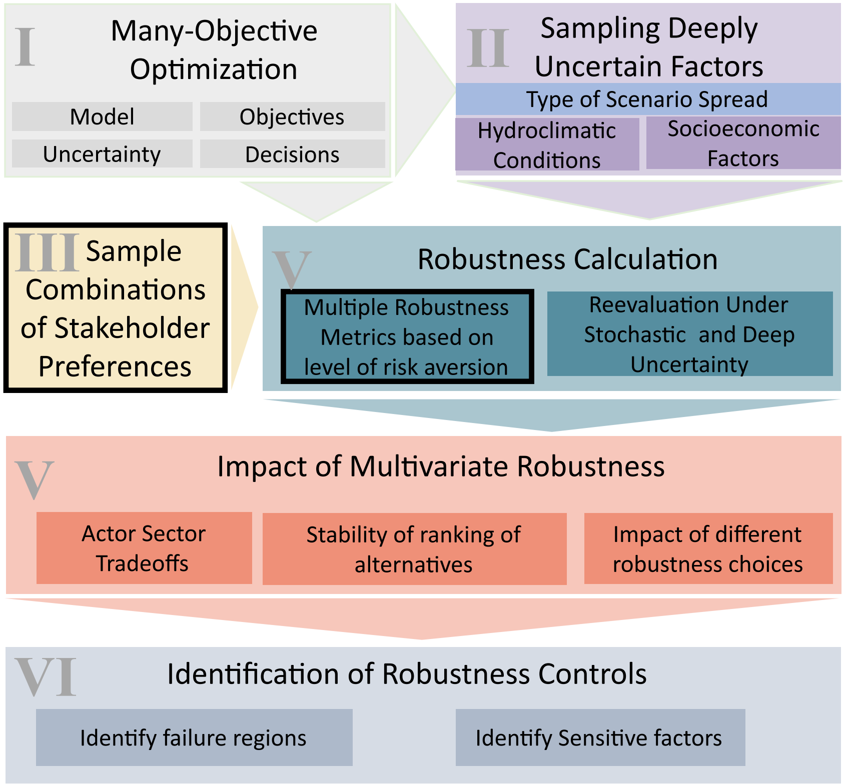

Figure 2. The six main stages in applying the Many-Objective Robust Decision Making (MORDM) framework to a decision problem. Black outlines highlight stages that include stakeholder preferences and their risk attitudes in the robustness assessment. This figure illustrates extension of MORDM framework adapted from the taxonomy of robustness frameworks presented in Herman et al. (2015).

(Section 3.5). Finally, we identify the main drivers of system failure from uncertainties explored and clarifying how choice of robustness definitions affect inferences related to consequential tradeoffs/vulnerabilities across stakeholder interests (Section 3.6).

Building on and extending McPhail et al. (2018), Figure 3 elaborates key steps in the exploratory evaluation of robustness considering candidate choices associated with stakeholder preferences, their risk attitudes and scenario generation methods. Robustness calculations require specification of deeply uncertain factors and their sampling strategies (ψ, purple boxes). Each deeply uncertain world will be characterized by stochasticity (s, green boxes). Each decision alternative, θ, is re-evaluated using the systems model to quantify values of multiple performance objectives (f, dark green boxes) representing preferences of various actors and sectors. The vectors of performance objectives can be combined in different ways to represent combinations of stakeholder preferences (m_1, m_2, …, m_n, yellow boxes). Finally, alternative representations of risk-attitudes in candidate robustness metrics are explored in terms of how they aggregate the performance of a decision alternative across sampled deeply uncertain states-of-the-world (SOWs, R_1, R_2, … R_m, orange box). In this way, we explore the influence of the choice of actor and sector combinations, decision alternatives, robustness metrics, number of scenarios, and type of spread of scenarios on robustness estimates. As noted by Hadjimichael et al. (2020), it is difficult in institutionally complex large-scale water resources systems for stakeholders to define and understand the implications of the alternative framings of robustness that could be considered. This study addresses this challenge by providing an exploratory framework that can broaden the representation of concerns while clarifying the consequences of incorporating them into alternative metrics of robustness. The following sections detail each of the key steps used to compute robustness.

3.1. Many-Objective Optimization

Veena et al. (2021) explored four problem formulations for the INS IBWT that quantified the tradeoffs across five system level objectives. The term "system-level" refers to the fact that the performance objectives were regionally averaged across the participating basins. The objectives included reliability, resilience, and vulnerability of water

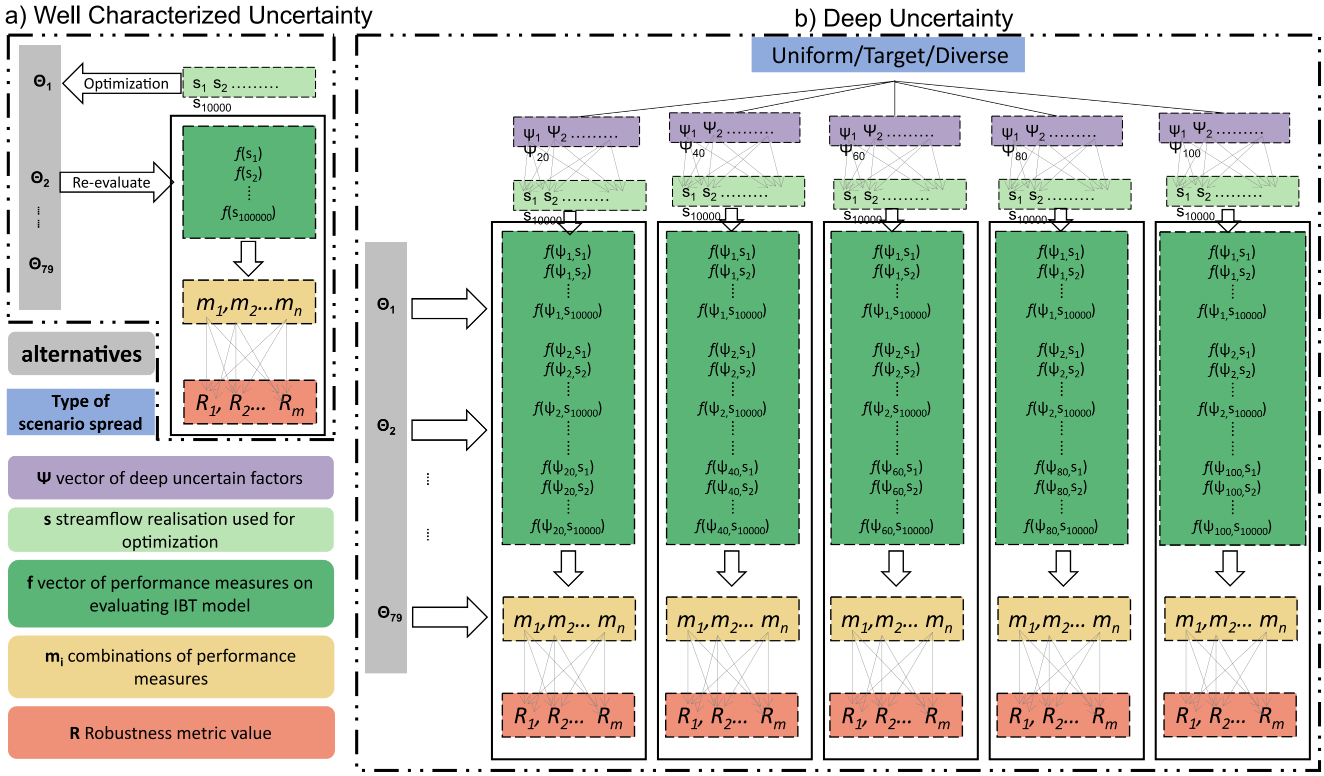

Figure 3. Evaluating the impact of metric definitions representing risk attitudes (orange), performance objectives (dark green), and their combinations (yellow) representing different stakeholders, and sampling strategies for stochastic (green) and deep (blue, purple) uncertainties on resultant robustness values. Shown are steps to quantify robustness under (a) well-characterized, and (b) deep uncertainties. Pareto-approximate alternatives (gray) are generated by many-objective optimization using stochastic streamflow realizations in (a). Each alternative is re-evaluated for a vector of performance objectives across a much larger stochastic set in (a). Deeply uncertain states-of-the-world cover the multi-dimensional factor space using uniform, target, and diverse scenario spread types (blue box in b).

demand satisfaction, reliability of maintaining MEF, and reliability of avoiding high flow exceedances. The formulations compare dynamic and adaptive rule-based operational designs against the status quo of no water transfer and a regional operational rule that has been suggested by the regional authorities, referred to as the proposed rule throughout the paper. To better understand the value of information coordination across the donor and recipient basins, two types of dynamic rules were formulated by Veena et al. (2021): noncooperative that only condition the transfer decisions on the states of the donor reservoir and cooperative that condition them on the states of both the donor and recipient reservoirs. Pareto approximate strategies were generated using evolutionary multi-objective direct policy search (EMODPS) considering stochastic uncertainty (or WCU) of inflows. Stochasticity is represented using 10,000 realizations of synthetic inflows (s_1, s_2, …, $s_{10,000}$) generated from historical inflows (1967–2012) (Herman et al., 2015; Kirsch et al., 2013; Veena et al., 2021) (Text S4 in Supporting Information S1). The procedure uses Cholesky decomposition to preserve the autocorrelation of inflows between the donor and recipient sites. *Cooperative* adaptive strategies outperformed all others indicating the importance of coordination between donor and recipient basins for managing water transfers and are, therefore, used in this study (79 in number) (Veena et al., 2021). Thus, we considered 81 INS IBWT operational design alternatives including the *proposed* and the status quo of *no-transfer*. These strategies are decisions (Step I in Figure 2, θ in Figure 3) to transfer water used for re-evaluating their performance under changing climates and demands to understand the long-term consequences of the INS IBWT for all the stakeholders involved. A brief overview of the model, objective functions, constraints and optimization procedure is included in Text S1–S3 and Table S1 in Supporting Information S1.

3.2. Sampling of Deeply Uncertain Factors

Here, we explore eight deeply uncertain factors (ψ, Figure 3) to capture potential impacts on river flows due to uncertain future changes in Indian Summer Monsoon precipitation patterns and demands; six related to inflows and two related to demands (Table 2, ψ in Figure 3). Demand factors are applied as multipliers to the historical

Table 2
List of Deep Uncertain Factors Used to Generate Scenarios With Change in Monsoonal Dynamics and Socio-Economic Changes

Deeply uncertain factors	Lower bound	Upper bound	Remarks
Log-space mean multiplier, inflows	0.95	1.05	Annual increase or decrease in mean annual inflows
Log-space std multiplier, inflows	0.5	1.5	Change in interannual variability of inflows
Log-space C_1 multiplier, inflows	0.5	1.5	Change in amplitude of annual monsoon
Log-space C_2 multiplier, inflows	0.5	1.5	Change in amplitude of semiannual monsoon
Log-space ϕ_1 delta (radians), inflows	$-2\pi/12$	$+2\pi/12$	Shift of annual monsoon
Log-space ϕ_2 delta (radians), inflows	$-2\pi12$	$+2\pi12$	Shift of semiannual monsoon
Demand factor, donor basin	1	1.5	Relative increase in donor demand
Demand factor, recipient basin	1	1.5	Relative increase in recipient demand

demands to represent candidate increases in the future. Six factors are used to generate different monsoon dynamics in the inflows including changes in log-space annual mean, log-space standard deviation and interannual variability of inflows. The equations to generate inflows from monsoon factor ranges are adapted from Quinn et al. (2018). Each deeply uncertain inflow defined by a combination of six monsoon related factors is paired with 10,000 realizations of inflows that represent WCU. The generated inflows are evaluated using available climate projections for the study region from the Inter-Sectoral Impact Model Intercomparison Project. These span five GCMs and four representative concentration pathways (RCPs) (Singh & Kumar, 2019; Warszawski et al., 2014) (Figure S1 in Supporting Information S1). These five GCMs cover a wide range of uncertainty for precipitation and temperature projections across the entire CMIP5 ensemble (Text S5 in Supporting Information S1) (McSweeney & Jones, 2016).

Deeply uncertain futures are sampled from within the space of plausible ranges of uncertain factors. We explore alternative sampling approaches that vary in how they focus on specific regions of the space or cover the entire space following McPhail et al. (2020). Vectors of the eight factors listed in Table 2 are generated using three sampling strategies—diverse, target, and uniform. Diverse sampling identifies locations of interest within the feasible range of uncertain factors, then generate samples around those locations (Anghileri et al., 2018; Giuliani & Castelletti, 2016; Haasnoot et al., 2012; Huskova et al., 2016; McPhail et al., 2018). This represents the general scenario generation approach followed in climate change impact studies where, first specific carbon emissions trajectories are specified, followed by using multiple climate models to generate possible climates for each trajectory. On the other hand, the targeted approach samples the scenario space such that different uncertain factors increase or decrease together monotonically (Beh et al., 2014, 2015a, 2015b). It follows that targeted sampling is useful in contexts where, changes in uncertain factors are highly correlated and would cover a smaller region of the overall feasible space. Finally, uniform sampling explores the entire multi-dimensional scenario space by sampling points within this space using Latin hypercube sampling (Herman et al., 2015; Kasprzyk et al., 2013; Kwakkel, 2017; Kwakkel et al., 2015; McPhail et al., 2018; Quinn et al., 2018; Singh et al., 2015). Further details on the generation of samples are provided in Figure S2 in Supporting Information S1. For each sampling scheme, 20, 40, 60, 80, and 100 samples of vectors are generated. The reader is encouraged to refer to McPhail et al. (2020) for more details on the distributional sampling of scenarios for targeted spread and diverse futures.

3.3. Sampling Combinations of Stakeholder Preferences

As detailed in Section 2, we explore 12 actor-sector combinations that represent the diverse stakeholders involved in the INS IBWT. To quantify the water supply related sectoral performances, the vulnerability measure (Vul) is used as follows,

$$Vul = \frac{\sum_{t=1}^{T}(ad_t - d_t)}{\sum_{t=1}^{T} ad_t} \times 100 \tag{1}$$

In Equation 1, d_t is the demand satisfied, ad_t is the actual demand, for each time period t, and T is the total number of time periods. The vulnerability measure can also be expressed in terms of average volumetric deficits by multiplying with the total demand. Preferences of the ecology-TV sector is quantified as the mean annual transfer

Table 3
List of Different Robustness Metrics Considered in the Analysis Along With Equations for Aggregation

Metri namec	Description	Method of combining multiple performance objectives (aggregation of "n" metrics)	Equation	Metric choice
Maximin	Worst-case performance	Worst case performance among "n" objectives	$min(minf_1(s), minf_2(s), \ldots, minf_n(s))$	Max
Maximax	Best-case performance	Best case performance among "n" objectives	$max(maxf_1(s), maxf_2(s), \ldots, maxf_n(s))$	Max
Laplace's principle of insufficient reason	Mean performance	Mean performance among "n" objectives	$mean(meanf_1(s), meanf_2(s), \ldots, meanf_n(s))$	Max
Minimax regret	The worst case of making a wrong decision in a given scenario	Worst case cost of wrong decision in any given scenario among "n" objectives	$max(max\ r_1(s), max\ r_2(s), \ldots, max\ r_n(s))$ $r_i(s_j) = max\left(f(s)\right) - f(s_j)$	Min

Note. The multi-objective version of each metric is applied when multiple performance objectives are included. In the equations listed, n denotes the number of performance objectives considered, f denotes objective function performance, s denotes the set of states-of-the-world (SOWs) in the analysis, a denotes the value to be evaluated across all alternatives and j denotes the jth SOW from the set of s. For example, considering the actor-sector combination in row eight of Table 1, two performance objectives considered in robustness calculations would be the vulnerability of water supply of donor (Godavari) and recipient (Krishna) basins. When evaluated across deeply uncertain scenarios, the worst value across donor and recipient basins would be selected for each alternative. The alternative with the maximum-worst off case would then be identified as most robust.

volumes for a water transfer alternative. The performance for the Ecology-MEF (J_{EF}) sector is quantified using a reliability measure as,

$$J_{EF} = \left(1 - \frac{\sum_{t=1}^{T} EF_t}{T}\right) \tag{2}$$

$$EF_t = \begin{cases} 1 & if\ (ef_t < mef_t) \\ 0 & else \end{cases} \tag{3}$$

where ef_t is the flow released as environmental flow and mef_t is the MEF at time t. MEF to be released downstream are set at 30% of the mean historical flow following recommendation by Smakhtin (2006). These sectoral performances are evaluated at the donor, recipient, and system level.

3.4. Robustness Metrics

Several robustness metrics have been developed and applied to analyze performance of complex water resources systems, each representing a unique way to attain aggregate performance rankings for alternative solution strategies across a large number of uncertain SOWs (Giuliani & Castelletti, 2016; Herman et al., 2015; Kwakkel, Eker, & Pruyt, 2016; McPhail et al., 2018, 2020). The means of computing these aggregations are important in how they tacitly indicate the risk attitude of the decision maker(s). Here, we illustrate four aggregation strategies for robustness metrics that have been commonly used in the literature and represent a range of risk-attitudes (in order of increasing risk aversion): the maximax, Laplace, minimax regret, and maximin metrics (Table 3). The maximax metric (i.e., "best") represents a low inherent level of risk aversion, as its calculation is only based on the best performance over all the scenarios. In contrast, the maximin metric (i.e., "worst") has a very high level of intrinsic risk aversion as it only considers the worst performance of all scenarios, leading to a very conservative solution (Bertsimas & Sim, 2004). Thus, across all decision alternatives, the alternative that has the maximum worst-off performance across all deeply uncertain scenarios is deemed to be most robust. Similarly, the minimax regret metric assumes that the selected decision alternative will minimize the largest regret possible, focusing again on the worst-case relative performance. Laplace's principle of insufficient reason, referred to as Laplace from hereon, is representative of a risk neutral metric as its calculation is based on the mean performance over all the scenarios considered. For each performance objective, values are estimated and rescaled between 0 and 1 to allow a comparison between objectives in calculation of robustness metrics.

When multiple actors and sectors are involved, the implications of performance aggregation across the actor-sector combinations as well as scenarios need to be explored carefully. Stakeholders and decision makers are not likely to know a *priori* the complex effects of aggregation or how to specify robustness metrics as noted in Hadjimichael et al. (2020). To better aid stakeholders in understanding the relative implications of alternative robustness metrics, we more carefully distinguish the conceptual definition of candidate metrics across how they are aggregated with respect to scenarios as well as performance objectives. For example, when applied to a single performance objective, the maximin metric would focus on the minimum ("worst") performance value across all scenarios. The multi-objective version of maximin selects the worst performing objective across all of the performance objectives as well as scenarios considered (Table 3). This version of the metric tracks maximal regret or loss across the four performance objectives across alternatives and scenarios. A total of 12 actor-sector combinations along with four levels of risk aversion result in 48 combinations of stakeholder interests and risk attitude assumptions.

3.5. Impact of Multivariate Robustness

A total of 432,000,000 robustness evaluations were carried out for each of the 81 alternatives. These result from a combination of 12 performance objectives, four robustness metrics, 300

(20 + 40+60 + 80+100) scenario sample sizes, 10,000 stochastic realizations, and three scenario spread types (Figure 3). Rank stability of alternatives across the candidate specifications of robustness definitions is evaluated 720 times, representing 12 performance objectives, four robustness metrics, five scenario sample sizes, and three scenario spread types. An alternative is ranked 81 if it attains the highest robustness value and 1 for the least robustness value. We summarize the rankings via the median and the interquartile range (IQR) of the ranks under WCU and DU sampling cases. A strategy is defined as having a stable ranking if there is little or no change in median rank defined under WCU and DU. We classify a strategy as having an unstable ranking when the difference in median rank between WCU and DU is greater than 20 or has high (>60) IQR rank under DU. We also explore the impact of these choices on the inferred stability of a strategy.

Along with the rank stability of a strategy, the degree of change in the quantified robustness of a transfer strategy when moving from the internal variability focus of WCU sampling to broader DU sampling could also be of interest to stakeholders. We define this change in terms of median and IQR rank of strategies. We classify the strategy as "improving" for an increase in median rank or decrease in IQR rank, "deteriorating" for a decrease in median rank or increase in IQR rank, or "similar" for a difference in median or IQR rank that falls within ±2 ranked slots of original WCU value. We also assess the impact of using various actor-sector combinations on resultant robustness perception of strategies. For the transfer strategies identified, we perform a detailed assessment of robustness controls to identify which factors among the many considered are driving robustness gradients across deeply uncertain scenarios (Step V, Figure 2).

3.6. Identification of Robustness Controls

This step identifies which deeply uncertain factors are most responsible for the failure of alternatives to meet the performance requirements implied for each of the different robustness metrics (robustness controls). We use Classification and Regression Trees (CART) (Breiman, 2017) to identify the relative importance of different factors for meeting performance requirements specified across alternative robustness metrics across sampled scenarios. CART requires input of the uncertain factors of focus and their performance outcomes (success or failure) (Step VI, Figure 2). The method then recursively partitions the factor space into subgroups to explain variation in failure or success outcomes (e.g., identifying the combinations of uncertain factors as well as their specific values that result in performance failures). Given that CART identifies the region of factor space that leads to failures, it facilitates scenario discovery where decision makers can more carefully pinpoint the most consequential scenarios of concern for a given INS IBWT operational design alternative. This step was completed using the "rpart" package to generate pruned trees and prevent overfitting using a ten-fold cross-validation process (Breiman et al., 1984; Therneau et al., 2010).

4. Results

4.1. Multi-Sectoral Performance of Transfer Strategies

We first analyze the multi-sector tradeoffs across the 81 water transfer strategies for the INS IBWT for the three sectors: ecology-TV, water supply, and ecology-MEF. Their performance is analyzed at the system level by estimating the average performances across both donor (Godavari) and recipient (Krishna) basins (Figures 4a and 4b). The system level performance of each strategy across all SOWs under WCU (DU) is plotted as a line crossing the three vertical axes, each representing a sectoral performance in Figure 4a (b). Across the 79 Pareto-approximate strategies, the average volumetric deficits ranged from 222 to 348 Mm^3 (2.4%–3.8% of total demands) for the water supply sector under WCU (Figure 4a). For these strategies, the reliability of maintaining MEF ranged from 97% to 98% for the ecology-MEF sector, while mean annual transfer volumes ranged from 4,985 to 7,730 Mm^3 for the ecology-TV sector, under WCU. Notable is the tradeoff between the ecology-MEF and water supply sectors at the system level, a 1% increase in MEF reliability requires a concurrent increase of 118 Mm^3 in average volumetric deficits. The *proposed* strategy results in the worst performance for the ecology-MEF (MEF reliability of 96.3%) and ecology-TV (mean annual transfer volume of 13,437 Mm^3) sectors. The *no-transfer* strategy results in the worst performance of the water supply sector with an average volumetric deficit of 1,547 Mm^3 (17% of total demands), respectively, at the system level. We surmise that the transfer of water between the Godavari and Krishna basins is likely to force decision makers to consider the significant tradeoffs between the water supply and ecology sectors in both basins.

On further analyzing these strategies under deeply uncertain futures, we find a substantial deterioration in the performance of the water supply and ecology-MEF sectors when compared to the narrower evaluation of performance under WCU (DU, Figure 4b). The average volumetric deficits across the Pareto-approximate strategies

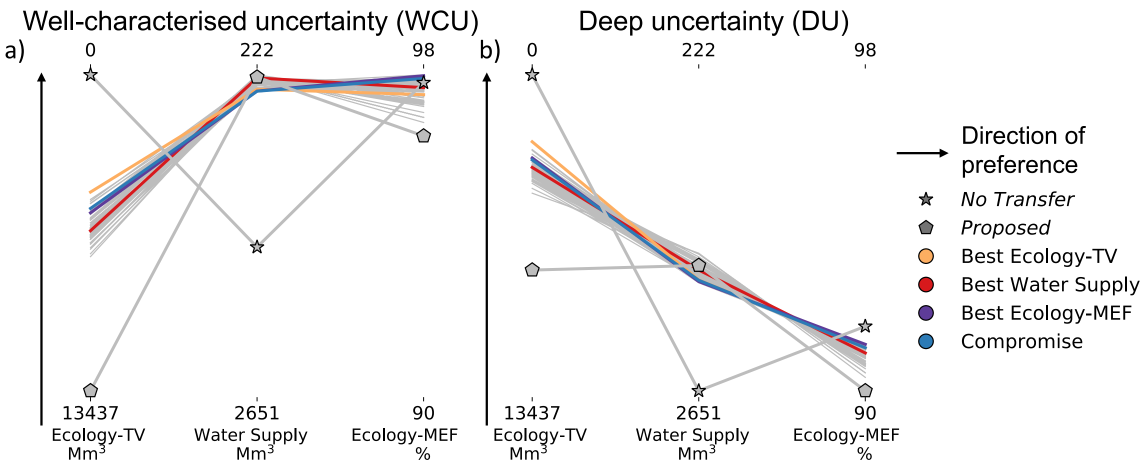

Figure 4. (a) Parallel coordinate plots showing performance of each sector for the system actor for all strategies under well-characterized uncertainty. Each vertical axis represents sectoral performance ranging from lowest (bottom) to highest (top) performance. Each strategy is represented by a line crossing the three axes. (b) Same as (a) but for all strategies reevaluated under deeply uncertain futures.

increase from 222–348 to 1,593–1,820 Mm^3 as we transition from an emphasis on hydroclimatic internal variability in the WCU evaluations to the broader uncertainties posed by climate and demand changes. Similarly, the reliability of maintaining MEFs reduces from 97% to 98% under WCU to 90%–91% under DU. The mean annual transfer volume reduces from 13,437 Mm^3 under WCU to 8,302 Mm^3 under DU for the proposed strategy. However, the annual volumetric transfers do not change substantially for the 79 dynamic state-aware solutions as they adapt to changing inflow and demand conditions under the DU SOWs. The *proposed* strategy attains a 90% reliability of maintaining MEF, the worst performance for the ecology-MEF sector under the DU SOWs across all strategies. The *no-transfer* strategy attains the highest performance for the ecology-MEF sector under DU futures but still results in the lowest performance for the water supply sector. Thus, even under the more challenging DU SOWs, the Pareto approximate strategies deteriorate less than the *proposed* and *no-transfer* strategies.

We further identify four strategies that represent different possible compromises between the three sectors at the system level. The *Best Water Supply strategy* attains the highest performance in the water supply sector from the system perspective under WCU (red line, Figure 4). This strategy is likely to be of high interest to all water users including farmers and urban centers as well as regional water planners who typically prioritize augmentation of freshwater supply. The *Best Ecology-MEF* strategy attains the highest performance for the ecology-MEF sector at the system level under both the WCU and DU SOWs (purple line, Figure 4). Considering the ecological services provided by the Godavari River downstream of the proposed Inchampalli dam site, these strategies would be of interest to ecologists and dependent downstream water users. The *Best Ecology-TV* strategy results in the lowest annual volumetric transfers from the Godavari to the Krishna river under both the WCU and DU SOWs (yellow line, Figure 4). This strategy would be of interest to stakeholders who would be concerned about the potential implications of mixing the waters of the Godavari with the Krishna, resulting in the introduction of new aquatic species in the Krishna River. It will also be of interest to stakeholders concerned with the cost of constructing and maintaining of the INS IBWT itself. The *Compromise* strategy represents the willingness of stakeholders to negotiate across sectors under both the WCU and DU SOWs (blue line, Figure 4). Together, these four strategies along with the *proposed* and *no-transfer* strategies, represent a range of stakeholders' interests including regional planning authorities, environmentalists, ecologists, water users, tribal populations dependent on MEFs, etc. We further examine these in more detail w.r.t to implied actor-sector tradeoffs as well as implications of robustness definitions.

4.1.1. Key Actor-Sector Tradeoffs Under WCU and DU

We now examine the tradeoffs between the three sectors for each actor perspective (donor-Godavari, recipient-Krishna, and system) associated with the INS IBWT to further understand the compromises faced by the participating basins (Figure 5). The average demand deficits for the water supply sector under WCU ranged from 24 to 33, 415–672, and 222–348 Mm^3 for the donor, recipient and system, respectively. The reliability of maintaining MEF, representing the ecology-MEF sector, ranges from 94% to 97%, 99% to 99%, and 97% to 98% under WCU for the donor, recipient, and system, respectively. A key tradeoff emerges between the ecology-MEF

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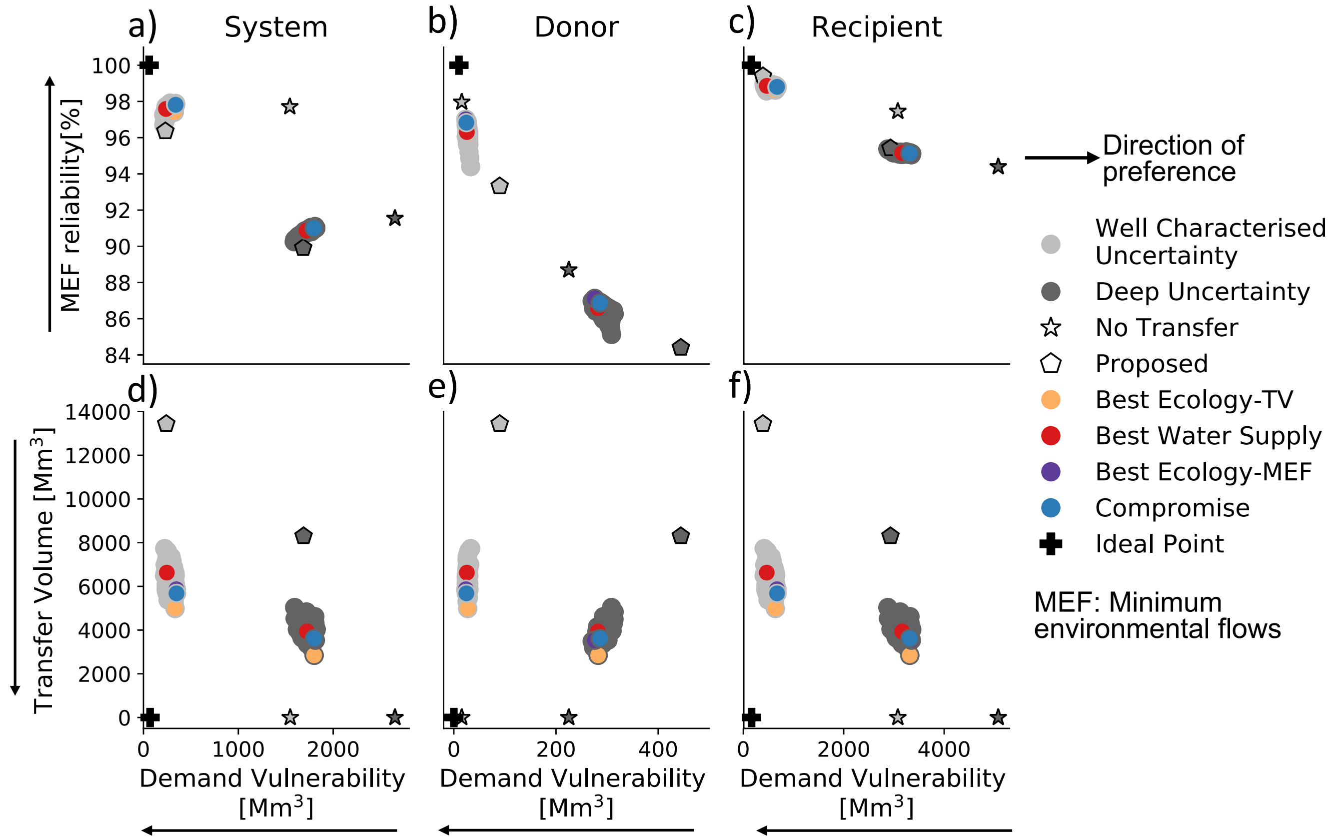

Figure 5. Trade-off between (a–c) vulnerability of water supply and reliability of maintaining MEF; (d–f) vulnerability of water supply and mean annual transfer volumes for (b, e) donor, (c, f) recipient and (a, d) system. The Pareto-approximate strategies are highlighted by circles. Performance under well-characterized uncertainties is shown by light gray circles while deep uncertainties in dark gray. MEF: minimum environmental flows.

and water supply sectors of the donor basin where increasing demand satisfaction by 9 Mm^3 is attained at the cost of 2% reduction in MEF requirements under WCU. Notably, the proposed strategy attains the highest performance (99.4%) in the ecology-MEF sector for the recipient-Krishna basin, but it does so by incurring a concurrent loss of MEF reliability in the donor-Godavari basin (93%). This results in the proposed strategy performing the worst for the ecology-MEF sector at the system level (96.3%). Thus, gains by sharing water between the Godavari and Krishna basins will entail a tradeoff between the water supply sector of the recipient-Krishna basin and ecology-MEF sector of the donor-Godavari basin, even when considering historical hydroclimatic variability.

The ecology-MEF sector witnesses a substantial system level performance reduction under DU futures, which is primarily due to the deteriorating MEF reliability of the donor-Godavari basin. Under DU futures, we observe a small reduction in MEF reliability for the recipient-Krishna basin despite an overall reduction in mean annual water transferred. This suggests that water transfers may alleviate some MEF shortages in the recipient basin. We also find a reduction in system level water supply performance under DU futures, driven primarily by substantial reduction in for the recipient-Krishna basin. Historically, the donor-Godavari basin has had lower demand and hence the impact on water supply performance is limited. Importantly, for all strategies, including *proposed* and *no-transfer*, a reduced performance for water supply and ecology-MEF sectors for all actors, and an increased performance for ecology-TV sector, is observed under DU futures compared to WCU. Reduced transfer volumes under DU compared to WCU is due to change in water availability and increased demands in both the basins.

4.2. Rank Stability of Strategies

Decision analysis frameworks should provide insights for how problem framing influences the preferential ordering of suggested actions across the diverse actors and sectors that have stakes. In our study, different robustness metrics represent alternative world views by exploring candidate performance goals across

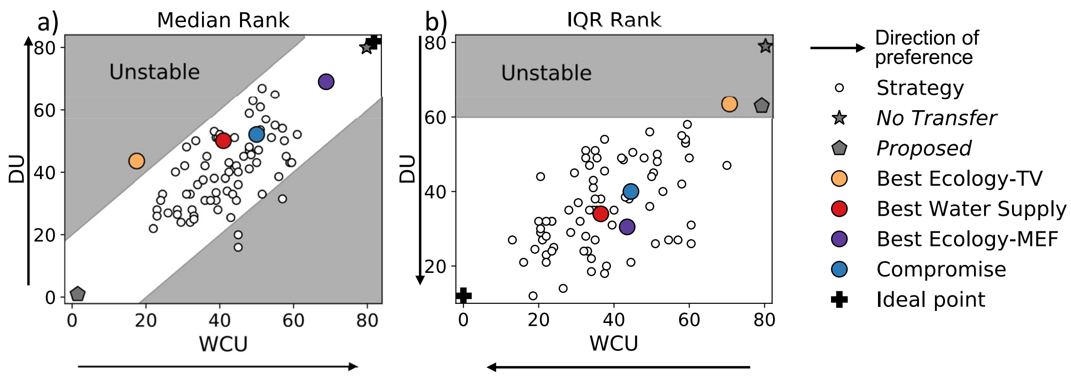

Figure 6. The (a) median and (b) interquartile range (IQR) of rank for a strategy under well-characterized uncertainties (WCU) (x-axis) and deep uncertainties (DU) (y-axis). A total of 81 strategies are ranked using 720 robustness metrics under both WCU and DU. The ideal point with highest median rank and lowest IQR is highlighted by a plus symbol in both panels. Gray shading represents regions of instability w.r.t strategy ranking. See text for more details.

actor-sector combinations and their risk attitudes. It further follows that each robustness metric is likely to result in a different rank ordering of decision alternatives. The rank stability of the decision alternatives may thus be an additional feature of interest to planners, especially in decision contexts where it is conceptually challenging to define the appropriate robustness metrics such as the INS IBWT. To investigate this, we plot the median and inter-quartile range (IQR) of the rank obtained by a strategy across all 720 robustness metric definitions under both WCU and DU (Figures 6a and 6b). A strategy with highest median rank and lowest IQR of rank indicates a high robustness irrespective of the choice of robustness definitions. The plausible highest rank in this study is 81 as there are 81 strategies and lowest is rank 1. Note that a strategy with high rank under WCU may not maintain its rank under DU. This can occur when a strategy is overly trained on historical data and exhibits a high-performance deterioration when exposed to DU futures. We further define a strategy as stable when the difference in median rank of WCU and DU is less than 20 or IQR rank of strategy is smaller than 60 under DU (shaded regions in Figures 6a and 6b). This choice of thresholds was determined after investigating the impact of different thresholds on resultant inferences of solution stability (Figure S3 in Supporting Information S1).

We find that the ranking of strategies is quite stable across the WCU and DU SOWs indicating that strategies tend to maintain similar relative performance under both cases (see also supplementary Figure S3 in Supporting Information S1). The stability of a strategy implies that the alternative robustness-based preferential ordering of that strategy is largely consistent across multiple worldviews. The *proposed* strategy attains low median rank and high IQR of rank suggesting an overall low robustness with high variability across robustness definitions. The *no-transfer* strategy attains the highest median rank across all robustness definitions under both WCU and DU SOWs but also exhibits a greater instability in ranking as indicated by its highest IQR in both cases. Table 4 summarizes the median rank, IQR of rank, as well as the stability ranking outcomes for the selected water transfer strategies. The Pareto-approximate strategies attain lower median ranks (i.e., higher median rank is preferred over lower ranks) when compared to the *no-transfer* strategy. They also maintain higher rank stability as exhibited by their low IQR (i.e., low IQR is preferred) as well as consistency of ranking between the WCU and DU SOWs. The *Best Ecology-MEF* strategy attains the highest median rank among the Pareto approximate strategies and has low IQR. The *Compromise* strategy has a relatively high median ranking, as well as lower IQR of rank under both WCU and DU SOWs. The *Best Ecology-TV* strategy is found to be unstable based on the criteria discussed above, which is mainly attributed to the poor performance of this strategy for the water supply sector. Overall, the selected strategies display advantages over one another either w.r.t individual sectoral performance or in rank stability across robustness choices. Ideally, a strategy with the highest median rank and lowest IQR of rank across the robustness definitions should be preferred. Such a strategy would maintain performance irrespective of the choice of actor-sector combinations and risk attitudes. However, we find that the median rank and IQR of rank have a trade-off across the set of strategies analyzed here. This indicates that strategies that attain a high rank across robustness metrics also display greater variability of ranking, resulting in lower performances in certain actor-sector combinations. Thus, choosing an appropriate water transfer strategy for the INS IBWT would be difficult and require careful consideration of involved tradeoffs under deeply uncertain futures.

Table 4
The Median and Interquartile Range (IQR) of Rank for Selected Strategies Under Well-Characterized Uncertainties (WCU) and Deep Uncertainties (DU)

		Median rank		IQR rank		Comment on stability		
Strategy name	Selection criteria	WCU	DU	WCU	DU	Difference in median rank of WCU and DU	Based on IQR rank of strategy	Whether median (IQR rank) improves from WCU to DU
Proposed	Baseline strategy	1.5	1	79	63	Stable	Instable	Similar (Improving)
No-transfer	Status quo	80	80	80	79	Stable	Instable	Same (Similar)
Best Ecology-TV	Strategy with minimum transfer volume under WCU and DU	17.5	43.5	70.5	63.5	Instable	Instable	Improving (Improving)
Best Ecology-MEF	Best performance for ecology-MEF under DU	69	69	43.5	30.5	Stable	Stable	Same (Improving)
Best Water Supply	Best performance for water supply under WCU and DU	41	50	36.5	34	Stable	Stable	Improving (Improving)
Compromise	Strategy with compromise performance across sectors	50	52	44.5	40	Stable	Stable	Similar (Improving)

4.3. Impact of Stakeholder(s) Interests and Risk-Attitudes on Perceived Robustness

A key objective of this study is to demonstrate how decision makers may explore different risk attitudes or stakeholders' interests in the evaluation of design alternatives robustness using the complex context of the INS IBWT. The exploratory evaluation of the consequences of the different risk attitudes across candidate robustness metrics can provide a broader context for how outcomes may be classified as being consequential across the range from full optimism to extreme pessimism. We visualize the variation of robustness values across actor-sector combinations, and risk attitudes for six selected strategies under DU SOWs as bar plots in Figure 7. We reiterate that across the candidate operational strategies for the INS IBWT, the preferred robustness for the Maximax, Laplace, and maximin metrics assumes maximization. Similarly, to choose the best robustness value for the minimax regret metric, the robustness values are subtracted from a value of 1 for consistency as this regret measure is minimized. Across all robustness metrics, the highest robustness value is attained by a variety of strategies depending upon the choice of actor-sector combination is emphasized. This shows that a single robust INS IBWT operational strategy cannot easily be identified without a deeper engagement with the trade-offs between different risk attitudes and carefully evaluating the choice of which actor-sectors that have a central role in decision making.

Figure 7 shows that the *no-transfer* strategy attains the highest robustness value compared to the other strategies across all levels of risk aversion for actor-sector combinations of donor water supply, donor ecology-MEF and system ecology-TV. It is expected that the *no-transfer* strategy results as being robust for the donor (Inchampalli) water supply and donor ecology-MEF combination as it avoids conflicts in resource sharing with the recipient basin. The *proposed* strategy is found to be robust for the recipient (Nagarjuna Sagar dam) water supply across all metrics and recipient ecology-MEF except for minimax regret. In summary, for donor related combinations, the *no-transfer* strategy is robust, while for recipient related combinations the highest metric value is attained by the *proposed* strategy. Not opting for the water transfer would be in the best interest of donor's water supply and ecology goals, while the *proposed* strategy entails the highest possible value of annual volumetric transfers. Similarly, for system ecology-TV which focuses on minimizing the transfer volume, the *no-transfer* strategy attains the highest robustness as the transfer volume is set to the minimum value of zero. Alternatively, system level actors for the INS IBWT are mainly decision makers focused on the overall average benefits across both the Inchampalli and Nagarjuna Sagar command areas.

As expected, the INS IBWT increases the robustness of water supply at the system level. Across all levels of risk aversion, the Pareto optimal strategies display greater robustness when compared to the *no-transfer* strategy for the water supply sector at the system level. Note also that at the system level, the robustness of strategies for Ecology-MEF sector is markedly different than for the water supply sector suggesting that stakeholders with a high preference toward the water supply sector may select strategies that pose higher risks for violating MEFs. The *no-transfer* strategy attains greater robustness compared to other strategies for the Laplace and maximin metrics at the system level for the ecology-MEF sector as well as across all actors and sectors ("All" in Figure 7). The Laplace metric captures risk-neutral mean performance across scenarios while the maximin metric captures

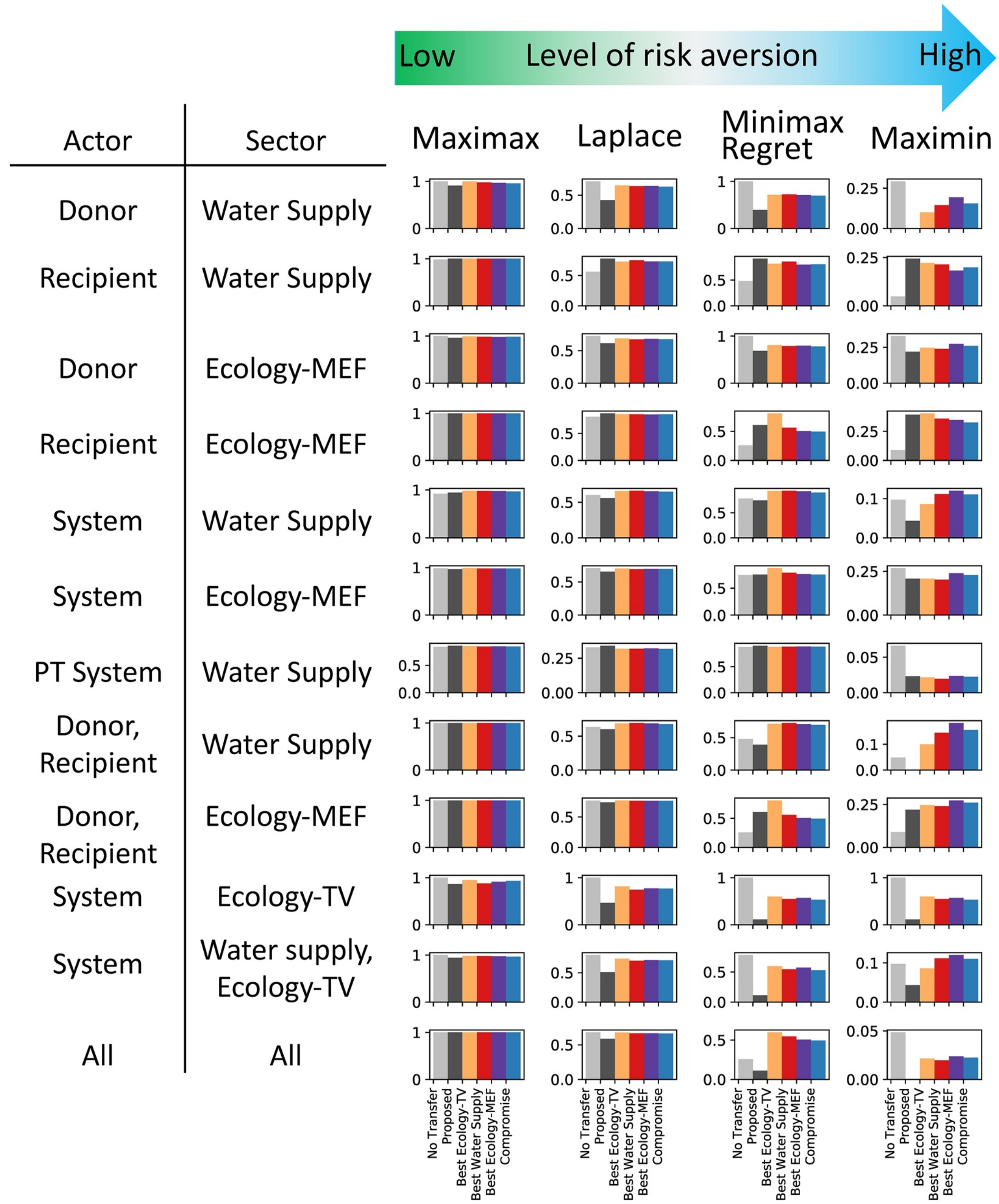

Figure 7. Robustness of selected strategies (from Table 1) for each combination of actor-sector and varying levels of risk aversion for uniform type sampling of scenarios. The arrow represents the increasing level of risk aversion with Maximax as least risk averse and maximin as highest risk averse.

risk averse performance. Among the optimal strategies, the *Best Ecology MEF* strategy attains high robustness for the maximin metric. The *Best Ecology TV* strategy attains the highest robustness when considering the minimax regret metric across all actors and sectors. Recall that this metric emphasizes alternative INS IBWT operational strategies that have minimal deterioration in their performance from an optimal baseline.

Metric combination number 12 (Table 4) represented as "All" in Figure 7 considers all actors and sectors related to the INS IBWT. This robustness assessment metric is more stringent and difficult to attain high levels of performance compared to other actor-sector combinations. However, it does identify INS IBWT operational strategies that are consistently classified as robust across the different levels of risk aversion. This consistency is partially an artifact of the compensatory effects of combining actors and sectors in the measure of robustness.

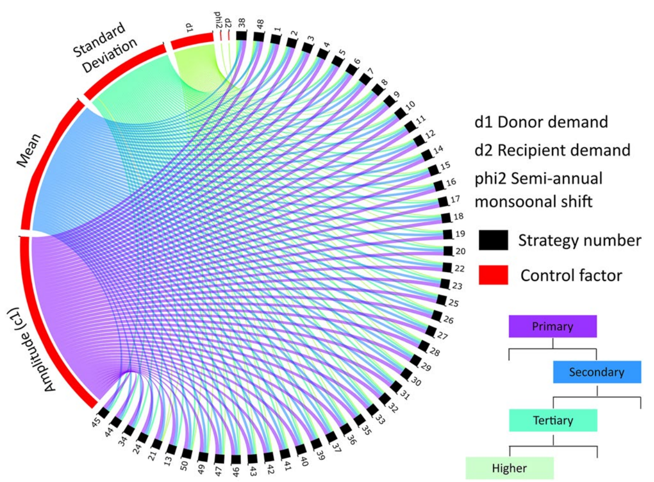

Figure 8. Understanding the importance of different uncertain factors on performance of optimized strategies using classification and regression trees. Shown are the ranking of deeply uncertain factors: changes in amplitude, standard deviation, demands in recipient, mean, demand donor and phase shift in determining robustness of strategies. Purple, blue, green, and lime green colors represent primary, secondary, tertiary, and higher factor ranking. The CIRCOS plot displays the uncertain factors as the circles outer edge in red and each optimized strategy is shown on the circle's outer edge in black. A purple line connecting a strategy to a factor indicates that factor being the primary control on strategy failure under deeply uncertain futures.

For example, the water supply sector may fail in certain scenarios, but those failures are in aggregate countered by increasing levels of success for the ecology-MEF sector. Overall, we find that assumed levels of risk aversion has a far more dominant effect on candidate robustness measures than the number of samples and type of sampling strategy (Figure S4 in Supporting Information S1). In summary, we find that the *no-transfer* strategy remains robust when considering donor water supply, donor ecology-MEF and system ecology-TV actor-sector combinations, across all deeply uncertain futures. On the other hand, the best water supply strategy performs the best for system water supply and donor, recipient water supply actor-sector combinations (Figure 7). Furthermore, when considered the most risk averse metric, the *no-transfer* strategy emerges as the most robust as it balances the deterioration in recipient water supply actor-sector against improvement in donor ecology-MEF and system ecology-TV actor-sector.

4.4. Influence of Deeply Uncertain Factors

Scenario discovery helps identify deeply uncertain factors, which drive the performance deterioration of objective functions and potential strategy failure. Here, we identify which uncertain factors control the robustness of transfer alternatives to DU SOWs using CART to perform scenario discovery for each of the 79 Pareto-approximate strategies (Step VI of Figure 2). As an example, we perform this analysis for the system level water supply metric, the actor sector combination 5 for a uniform sampling of scenarios (Figure 8). Notably, the order of influence of the deeply uncertain factors on strategy failure is found to be the same across all strategies: amplitude of inflows to the donor and recipient basins, mean inflows to the donor and recipient basins, standard deviation of inflows to the donor and recipient basins and demands in the donor basin. Climate models struggle to reproduce the complex spatio-temporal patterns of the Indian Summer Monsoon (Kodra et al., 2012; Konduru & Takahashi, 2020; Saha et al., 2021), but understanding potential future river flows is crucial to understanding potential strategy failure. Our analysis suggests an urgent need to focus on understanding the potential temporal dynamics of future hydro-climatology of this region given its significantly important role in influencing strategy failure.

5. Conclusion

We apply an innovative framework to a major water transfer project in India, to illustrate how the role of different sectoral priorities, stakeholder preferences, policy options, uncertainties and robustness metrics, affect robustness assessments. This study contributes a proof-of-concept to demonstrate how evolving analytical frameworks can support infrastructure planning and decision making under uncertainty. Our results reveal how tacit assumptions within robustness metrics could influence the perceived robustness of INS IBWT policies. We find stronger variation in robustness values across different risk-attitudes and actor-sector combinations compared to sampling choices. Different actor-sector combinations may yield different robustness values of selected strategies. For example, when risk averse measures of robustness are applied to donor favored measures of system performance, we find that the *no-transfer* strategy has the highest robustness. Alternatively, the *proposed* transfer is also identified as the highest rank for a selected stakeholder preferences which are recipient centered. Our analysis suggests that while the high-cost INS IBWT infrastructure investment may be considered feasible under historically observed stationary climatic conditions, that future climate change effects have the potential to strongly degrade its robustness performance across all of the operational strategies and actor-sector concerned assessed. In assessing the robustness of the INS IBWT, the distribution of scenarios has a greater impact on the inferred robustness values versus the number of scenarios considered, in agreement with prior analysis by McPhail et al. (2020). Overall, this study highlights the importance of an exploratory evaluation of the robustness of mega-investments projects.

The choice of robustness metric presents a daunting challenge for the complex decision context of the INS IBWT. It follows that an easy to attain performance goal will lead to high robustness values while a stricter performance requirement that maintain key system performance goals may result in lower robustness values. The ranking across robustness metrics therefore does not distinguish the relative value or importance of the underlying metrics to real operations, but rather the consequences of risk attitudes and stakeholder preferences. This could be altered in future studies with stakeholder elicitation to discover acceptable and stricter performance values. For example, the *proposed* strategy attains 90% reliability of maintaining MEF under the DU SOWs which is the worst performance compared to other strategies. Here, the contention between different decision makers on the acceptable level of risk emphasizes that future work would need to clarify the accepted value of reliability or other performance requirements. In other words, 90% reliability may be seen as a failure or sufficient across diverse decision makers.

In this study, we constructed combinations of actor-sector preferences based on an understanding of the stakeholders involved in the INS IBWT. The exploratory robustness assessment framework contributed here has significant potential to provide a quantitative basis for stakeholder elicitations using a participatory modeling framework and aid in building a shared understanding of potential irreversible decision lock-ins. Such participatory approaches require inclusive thinking to account for different worldviews, priorities and preferences of marginalized communities and avoiding the monopolization of project benefits (Eriksen et al., 2021). While we know that the "planners" associated with this project want to minimize system level deficits and that all stakeholders are neither well represented nor consulted, there are issues regarding their understanding of decision analysis terminology and techniques. So, to facilitate an appropriate uptake of such approaches, it will require investments in building capacity and understanding of robustness, uncertainty, risks, and participatory stakeholder engagement. Additionally, research on the applicability and usefulness of approaches such as dynamic planning, will help improve the design and management of institutionally complex water resources systems balancing conflicting demands and complex interdependent risks.

Recent research has highlighted the complex nature of IBWTs and their multi-faceted challenges. We contribute to this growing body of literature by highlighting the type of information that advanced decision support can provide for better engaging a variety of stakeholders. This framework could also be extended to other robustness metrics such as satisficing criteria and higher-order moments. Analyzing the robustness of alternatives against different thresholds using the satisficing criteria, usefully indicates their stability and is worth exploring, especially during participatory engagement. Stakeholders may implicitly favor one actor-sector over others because of hidden assumptions within their robustness analysis. The framework in this paper offers a means of revealing those hidden assumptions and making the decision process transparent. This has benefits of (a) ensure stakeholders are not blind to potential risks and trade-offs and (b) aid the co-production process by providing insight into the implications for all actors-sectors. The methodology introduced in this study is widely applicable to other large infrastructure planning projects with multiple stakeholders and multisectoral implications.

While the exploratory robustness assessment framework contributed in this study may be considered rather complex in the way it compares alternative strategies for deeply uncertain futures, it provides a wealth of decision relevant information that would not available from more traditional planning methods. Typically, practitioners rely on scenario analysis or probability distributions to characterize future uncertainties. However, in absence of an understanding of which probability distributions to use or how to parameterize them, robustness analysis is valuable for enabling stress testing of management strategies against deeply uncertain futures (Singh, 2023). By exploring diverse definitions of robustness, we enable stakeholders to better understand the implications of their levels of risk aversion and potentially competing interests in defining consequential outcomes across the sectors and actors involved in institutionally complex decision contexts such as the INS IBWT considered here. Our framework for exploratory assessment of system robustness provided insights that would be missed in simplified abstractions of the INS IBWT.

We found that not transferring water between the basins (i.e., using the no-transfer strategy) is a robust alternative for half of the actor-sector combinations considered. On the other hand, a robustness definition focusing on system level reliability of water supply would rate this option as inferior to other water transfer alternatives. Thus, by using multiple definitions of robustness that consider a range of actors and sectors, we were able to show for which particular actors and sectors the INS megaproject may be considered an inferior option when compared to within-basin measures to augment water supply or reduce demands. This information is important as generally robustness analysis presume actor-sector combinations and interpret strategy performance accordingly.

We also identified a compromise strategy from across the 79 Pareto approximate strategies that balances performance between actors and sectors, irrespective of choice of robustness metrics. This strategy would and its tradeoffs context would not be discovered by stakeholders using a simpler aggregated system-level cost-benefit analysis, and the insights gained from our exploratory robustness analysis provides a rich context for stakeholders to evaluate their own perceptions of INS IBWT's utility as well as its impacts (positive and negative). Our exploratory scenario discovery reveals that variations in monsoonal amplitude is the most important uncertain factor that controls failure of a majority of water transfer strategies under deeply uncertain futures. This type of sensitivity analyses identifies the cause of failure and the variation across policies. The framework allows decision-makers to map actions to consequences from different stakeholder perspectives, identifying drivers of failure in large infrastructure projects, and questioning the necessity of the project. Overall, this study is used to highlight the dire need to do these complex analyses for understanding the consequences of investment decisions when there are no simple relationships between decisions and outcomes.

Data Availability Statement

All code for replicating the analysis and figure generation can be found at https://doi.org/10.5281/zenodo.7470815. DOI: https://doi.org/10.5281/zenodo.7470815 (Sunkara, 2022). The inflow time series for the donor basin was obtained from Central Water Commission (CWC) requesting the data in this link https://cwc.gov.in/get-hydrological-data and the recipient reservoir (Nagarjuna Sagar) was provided by Irrigation and CAD department, Telangana (https://irrigation.telangana.gov.in/icad/contact).

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