

1 **Quantifying the value of stakeholder elicited**
2 **information in models of coupled human-water systems**

3 **Sai Veena Sunkara¹, Riddhi Singh^{1,2}, and Ajay Bhawe³**

4 ¹Department of Civil Engineering, Indian Institute of Technology Bombay, Powai, Mumbai 400076.

5 ²Interdisciplinary Programme in Climate Studies, Indian Institute of Technology Bombay, Powai, Mumbai
6 400076.

7 ³School of Engineering, Newcastle University, Newcastle, United Kingdom.

8 **Key Points:**

- 9 • We develop socio-hydrologic models (SHMs) to capture human-water interactions
10 in the operation of Nagarjuna Sagar reservoir in Southern India
11 • We assess the sensitivity of SHM structures to varying levels of stakeholder elicited
12 information
13 • Stakeholder elicited SHM structures improve reproduction of reservoir storage

Abstract

Causal loop diagrams (CLDs) based on expert and/or stakeholder inputs inform the quantitative structure of socio-hydrological models (SHMs). However, a systematic exploration of the sensitivity of CLDs and SHMs to different levels of stakeholder inputs is lacking. For a large multi-purpose reservoir in southern India, we explore this sensitivity by developing three CLDs that integrate reservoir water balance, groundwater pumping, and consumer water use patterns. CLD1 is a conventional water balance-based reservoir model, while CLD2 additionally incorporates the reservoir operator’s judgment and groundwater pumping. CLD3 further incorporates the adaptive behavior of water users by adjusting demands in response to long-term (5-year) droughts. The correlation between observed and simulated monthly reservoir storage (2000-2013) for SHM1, SHM2, and SHM3 is 0.57, 0.85, and 0.87, respectively. SHM3 also outperforms SHM1 and SHM2 in simulating the relative use of surface and groundwater for irrigation purposes in the command area of the reservoir. Simulated demand deficits, command area groundwater levels, and minimum environmental flow satisfaction downstream of the reservoir for 1968-2013 using the three models exhibit substantial differences. SHM1 and SHM2 simulate deteriorating groundwater levels under the multi-year drought of 2001-2003 while SHM3 does not due to the consideration of adaptive farmer behavior. Thus, our understanding of water and food security during a multi-year drought can be significantly affected by the level of stakeholder inputs incorporated in the models. We highlight the importance of testing different SHMs structures to better understand human-water interactions under extreme conditions.

1 Introduction

Human interference in the natural hydrological cycle has increased in the Anthropocene. This has led to methodological developments to understand and model the dynamics of coupled human-water systems (Du et al., 2020; X. Li et al., 2018; Noël & Cai, 2017; Merz et al., 2020; Sivapalan et al., 2012; Cai et al., 2015). Several studies focus on feedback and interactions among water resource systems and human behavior in relation to floods, droughts, water supply, and groundwater exploitation. Exploring complex human-water interactions requires understanding of human behavior, changes in biophysical and socio-economic systems, and evolving water resources management strategies, all of which are central to addressing the interlinked Sustainable Development Goals (Di Baldassarre et al., 2019). Socio-Hydrological Models (SHMs) quantitatively couple social and hydrologic processes, and can help to explore the complex decision context of several water resource systems (Di Baldassarre et al., 2021; Herrera-Franco et al., 2021; Troy et al., 2015; Yu et al., 2020; Khadim et al., 2023). They allow the modeler to explore the dynamic co-evolution of coupled human-water systems by abstracting salient features of both systems (Sivapalan et al., 2012). They have been applied to enable decision-making at farm scale, understand system dynamics, and identify trade-offs between environmental and economic measures (Foster et al., 2014; Inam et al., 2017; Van Emmerik et al., 2014; Pande & Savenije, 2016; O’Keeffe et al., 2018; Wescoat Jr et al., 2018; Ghorishi et al., 2021).

Development of a causal loop diagram (CLD) is a critical step during the qualitative phase of studying system dynamics for human-water interactions (Gohari et al., 2013; Ram & Irfan, 2021). CLD integrates multiple elements of the water resources system including human, ecological and hydrological aspects. Often CLDs are conceived using existing data and the modeler’s knowledge of the system (Gohari et al., 2013; R. Li et al., 2018; Ram & Irfan, 2021; Daniel et al., 2021). However, a few studies have highlighted the value of multi-stakeholder input for developing CLDs that capture a range of feedbacks and interactions. Examples include analyses of conflicts in policy-making for groundwater protection (Giordano et al., 2017), an economic view of the urban water system (Mbavarira & Grimm, 2021), examining water-food-energy nexus systems (Purwanto

et al., 2019), hydropower projects (Voegeli & Finger, 2021), and water quality management (Halbe et al., 2018). For example Giordano et al. (2017) identified interactions between individual perceptions of farmers, regional water managers, and an irrigation consortium. They showed how decisions from regional water managers impact farmers' behavior and the probable mechanisms through which water pricing drives groundwater exploitation from illegal pumping activities.

While CLDs provide a useful conceptual representation of a system, a CLD-only approach without model-based simulation may be insufficient for risk assessment and decision making (Blair et al., 2021). SHM development from CLDs that are informed by stakeholders is now accepted practice, but with evolving methodologies. Approaches include eliciting data for each CLD element (Blair et al., 2021), using group exercises with stakeholders to understand the complexity of Water-Energy-Food systems (Purwanto et al., 2021), and collecting primary data on water consumption and irrigation scheduling using semi-structured interviews (O'Keeffe et al., 2018). However, SHMs are not always validated using observations for key state variables (Troy et al., 2015; Wine, 2020; Ross & Chang, 2021). In some cases, models are validated using limited period information, or from other sources like newspaper articles (Chen et al., 2016; Elshafei et al., 2015; D. Li et al., 2019; Wei et al., 2017). Sometimes the model is developed and not validated due to unmeasured/intangible variables in the model or lack of observational data (Sung et al., 2018; Müller & Levy, 2019; Kandasamy et al., 2014). An adequate representation and simulation of the dynamics of the socio-hydrologic system is necessary to derive insights on the feedback between human and water systems (Elshafei et al., 2014; Di Baldassarre et al., 2015). Therefore, although validating complex SHMs is daunting, there is a recognized need to find appropriate methodologies (Kwak et al., 2021), such as use of proxy variables (Roobavannan et al., 2017).

As SHMs represent diverse hydrologic and socio-economic, and human-water interactions, model development and validation are by definition study area specific. Here, an important question arises - how much stakeholder information is needed to arrive at a decision relevant representation? The answer is perhaps partly related to protocols for validating SHMs. Here, we explore a methodological approach to SHM development that uses a multi-model framework that systematically increases the incorporation of stakeholder information across model structures. These structures are then evaluated using observations of key state variables to arrive at their relative representativeness of the system. We apply this framework to understand the dynamics of a large multi-purpose reservoir in southern India for the historical time periods. The main contributions of our study are:

1. We explore how stakeholder information can be included in a systematic manner using multiple CLDs and the implications of the resultant SHM structures on the state of the socio-hydrological system being studied.
2. For a large-scale multi-purpose reservoir in India, we evaluate the ability of available data in helping identify a representative SHM.
3. We analyse downstream environmental flows, water shortages, and groundwater level in the command area of the reservoir using all SHMs to highlight the degree to which our interpretation of the human-water interactions may differ across model structures.

2 Study Area and Data Sources

The Nagarjuna Sagar (NS) reservoir is one largest and most important irrigation projects in the Krishna basin, a major river basin in Southern India. NS has a storage capacity of 5,733 Mm³, which is around 20% of the average annual inflow at the reservoir site for 1968-2016. It sustains a large community of farmers with an irrigable area of ~9,000 km². Historical data shows substantial upstream developments that have im-

117 pacted volumetric inflows into the reservoir (Table 1). Compared to available water and
 118 storage, water demands on the NS reservoir are quite high with total annual demand of
 119 8,535 Mm³. The reservoir water is used for irrigation, domestic and industrial water sup-
 120 ply. Since 2004, NS supplies ~123 Mm³ of water annually to Hyderabad, a pharmaceu-
 121 tical and software hub with more than 7 million inhabitants, and is expected to increase
 122 supply to 370 Mm³ by 2030 (Molle et al., 2010; Van Rooijen et al., 2005). Marginal and
 123 small farmers account for 60% of the area operated by holdings in the NS command area
 124 (Figure S1 in Supporting Information S1). Upstream changes may have contributed to
 125 the severe drought period of 2002-2004; the longest contiguous drought within the 1969-
 126 2010 period (Venot et al., 2007), and may further increase the potential for future droughts
 127 (Biggs et al., 2007; Gaur et al., 2008). The NS reservoir is committed to supplying 2,264
 128 Mm³ to the Krishna Delta (irrigated area of 5,400 km²) (Molle et al., 2010). Hence, the
 129 NS reservoir faces severe challenges in meeting increasing multi-sectoral demands. This
 130 situation has precipitated into a proposal of a major inter-basin water transfer project,
 131 within the larger National River Linking Project, that aims to increase water availabil-
 132 ity to the NS reservoir by transferring around 16,400 Mm³ of water from the Godavari
 133 River basin (NWDA, 2021). A majority of these transfers are prescribed during mon-
 134 soon and post-monsoon seasons.

135 **3 Methodological Framework**

136 Broadly the methods follow the steps detailed in Figure 2. We begin with the concep-
 137 tualization of the NS reservoir system without any stakeholder information. The ini-
 138 tial model structure along with various sub-modules is described in section 3.1. Next, semi-
 139 structured interviews are performed to gather stakeholder information. The procedure
 140 followed for conducting the interviews is detailed in Section 3.2. The information from
 141 these interviews is used to develop alternative CLDs. Finally, SHMs based on the three
 142 CLDs are validated against observations of key state variables and water security met-
 143 rics are used to understand the conditions on the project’s command area (Section 3.3).

144 **3.1 Preliminary Conceptualization of the NS reservoir: CLD1**

145 Causal loop diagrams (CLDs) help conceptualize the system by defining and con-
 146 necting key elements, thus enabling a comprehensive understanding of interactions (Serman,
 147 2000; Simonovic, 2009). To develop the pre-interview CLD (CLD1), the analyst concep-
 148 tualizes the natural hydrologic processes and associated human interferences without any
 149 stakeholder interaction. In the context of the NS reservoir, this includes identifying rainfall-
 150 runoff module, reservoir water balance and operating policy, and water use patterns in
 151 the project’s command area (Figure 3). This CLD is developed without any stakeholder
 152 inputs but relies on historical data, the analyst’s understanding of the system, and the
 153 assumption that the reservoir will be operated following a rational scheme that releases
 154 water for demand satisfaction followed by release of any excess water exceeding reser-
 155 voir’s live storage capacity.

156 The CLD includes reservoir module, and command area module. The reservoir mod-
 157 ule includes the human elements of reservoir operation that is prescribed using standard
 158 release rules (Section 3.1.2). Inflow from the river is the input to the reservoir module,
 159 which is assumed to be determined by natural rainfall runoff processes. Ideally, one would
 160 start with a rainfall-runoff model, but we have inflow data and so do not include it here.
 161 We assume that reservoir operators will release water as per the estimated demands. The
 162 command area module tracks demand deficits based on aggregate domestic, industrial,
 163 and agricultural water demands.

Table 1. Different historical characteristics of the NS reservoir.

Characteristic	Variable	Value	Data source
Hydro-climatology	Mean annual precipitation, temperature (catchment area)	760 mm (1901-2015), 26°C (1951-2015)	Srivastava et al. (2009); Pai et al. (2014)
	Potential evapotranspiration	1767 mm (1951-2015)	Srivastava et al. (2009); Hargreaves and Samani (1985)
	Average annual inflow	43323 Mm ³ (1967-1981), 26608 Mm ³ (1982-2015)	Irrigation and CAD department, Telangana
	Major drought in historical time period	2001-2004	Precipitation based
Reservoir related	Maximum storage capacity	5733 Mm ³	Irrigation and CAD department
	Storage data [monthly, 2000-2020]	Average monthly storage 3375 Mm ³	WRIS (www.india-wris.nrsc.gov.in)
Command area related: Land use, Socio-economic conditions	Land use in command area for Year 2005	Cropland: 80% Forest: 12% Water bodies/wetlands: 5% Others: 3%	Roy et al. (2016)
	Construction of large dams (Name, year)	Srisailam (1981), Narayanapura (1982), Jurala (1996)	Lehner et al. (2011)
	Groundwater	Area average of 47 well data (Figure 1)	WRIS (www.india-wris.nrsc.gov.in)
	Population in command area (2011 Census)	~216030	2011 census
	Irrigation demands	7000 Mm ³	Veena et al. (2021)
	Domestic water supply demands	550 Mm ³	Veena et al. (2021)
	Industrial demands (assumed equal to domestic)	550 Mm ³	Veena et al. (2021)
	Economic condition in Krishna basin (purchasing power parity)	+98% from 1990 to 2005	Nordhaus and Chen (2016)
	Irrigated area	11822 km ²	Veena et al. (2021)

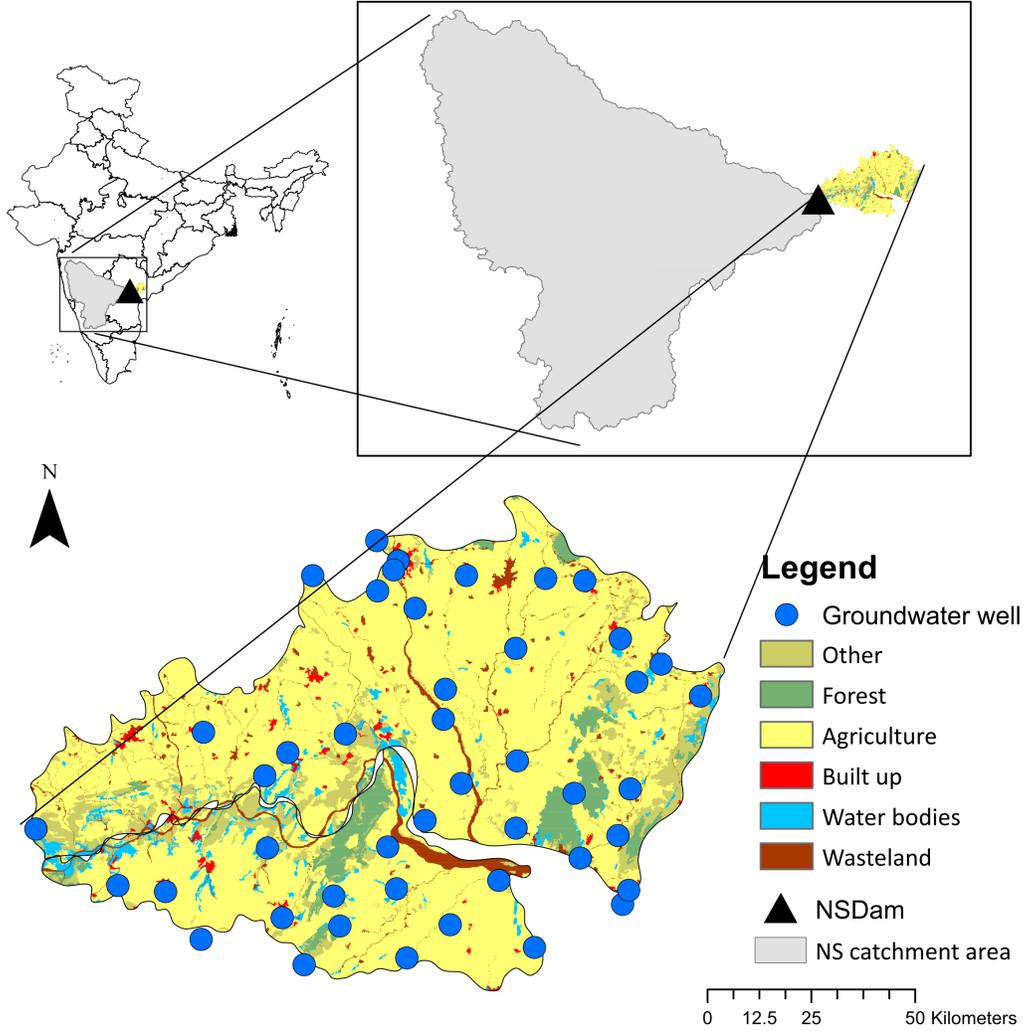


Figure 1. The Nagarjuna Sagar reservoir, its catchment area, and command area. Land-use pattern in the command area is shown where majority is agriculture. The location of groundwater wells is shown in blue circles.

164

3.1.1 Reservoir Module

The reservoir model tracks the water balance dynamics of reservoir via Equation 1.

$$s_t = s_{t-1} + q_t - d_t - re_t \quad (1)$$

165

166

167

168

169

170

171

172

In Equation 1, s_t is the storage in the reservoir, q_t is the inflow to the reservoir, d_t is water released for satisfying multisectoral demands and re_t is the excess water released downstream. Subscript t is the timestep. The model is simulated on a monthly timescale. Without any stakeholder elicitation, water is released assuming a rational decision maker. First, demand related releases are made, then excess water is released if s_t exceeds 95% of live storage capacity of the reservoir. These releases are monitored for high flow failures defined by the maximum release in the historical data for a given time period.

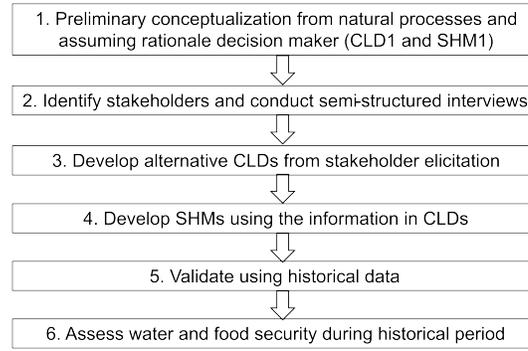


Figure 2. The methodological framework for developing alternative CLDs and SHMs from first principles and stakeholder elicitation. This is followed by validation using historical data.

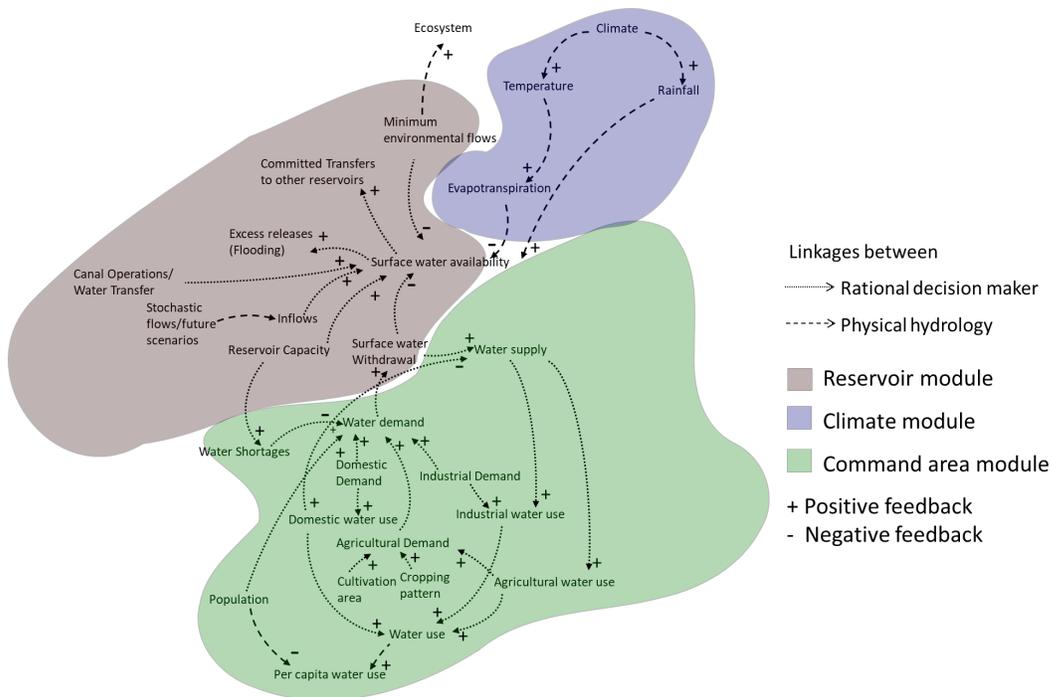


Figure 3. CLD1 showing the preliminary conceptualization of the NS reservoir system with three main components: the reservoir operation module, the command area module and climate module.

3.1.2 Command area module

173

174

175

176

177

178

179

180

181

182

This module specifies demands that are to be satisfied from reservoir releases and groundwater pumping. Demands are estimated for domestic, agricultural and industrial sectors as a function of time. Agricultural demands depend upon crop type, cropping area and net irrigation requirements, which are estimated using historical observations for 1968-2013 (Gaur et al., 2008; Venot, Reddy, & Umapathy, 2010; EPTRI, 2008). Domestic demand is based on population (Jones & O’Neill, 2016) and per capita demand. In absence of data, the industrial demands are assumed equal to domestic demands. Supplementary Figure S3 shows the demand patterns for 1968-2013. Cropping is sown in two major seasons Kharif (July to November) and Rabi (December to April). Type of

183 crops in Kharif season are rice, groundnut, sorghum, grams, cotton, chilli, and in Rabi
 184 season are groundnut, sorghum and grams. Cropping pattern is 25%, 12%, 10%, 29%,
 185 17%, and 6%, for crops rice, groundnut, sorghum, grams, cotton, chilli in both seasons.

186 **3.2 Stakeholder Elicitation**

187 We apply a stakeholder elicitation approach to characterise the role of human de-
 188 cision making in managing water resources. Inputs from stakeholders can help identify
 189 and characterise water management decisions of different stakeholders and incorporate
 190 their insights into the model structure (Bhave et al., 2018, 2020; Jacobs & Buijs, 2011).
 191 This is especially relevant for multi-stakeholder systems such as large multi-purpose reser-
 192 vvoirs because interactions between hydrological, infrastructural, and human behavioral
 193 dimensions are complex, and capturing such interactions may be crucial to simulate con-
 194 ditions accurately (Jacobs & Buijs, 2011). Here, we divided stakeholders into three groups
 195 based on their role in decision-making related to the NS reservoir. Group 1 comprised
 196 of government decision makers who take decisions regarding reservoir management such
 197 as state irrigation departments. Group 2 comprised of water users in the study area, in-
 198 cluding municipal bodies that manage water for Hyderabad and farmers in the project’s
 199 command area. Decisions of stakeholders from the second group are affected by the de-
 200 cisions/actions of the first group. Group 3 comprised of stakeholders concerned about
 201 the riverine ecosystems such as non-governmental organizations (NGOs).

202 We use semi-structured interviews to elicit responses to specific questions of the
 203 interviewer (the first author) and to allow for a more organic discussion that yields in-
 204 formation on other dimensions that could help improve the relevance of the CLD for this
 205 complex system. These interviews were conducted between May and July 2019; 8 with
 206 the first group, 9 with the second group and 4 with the third group. Interviews were con-
 207 ducted in person at the stakeholder’s workplace, with due consent and anonymity, and
 208 lasted between 30 minutes to 1 hour. Each interview started with an informal social dis-
 209 cussion and a brief introduction to research goals and interview style. Questions were
 210 open-ended and based on a pre-interview questionnaire. The pre-interview questionnaire
 211 included questions on water availability, cropping patterns, tackling water deficits, chal-
 212 lenges related to managing water resources, water transfers, prioritization of donor and
 213 recipient basins, groundwater withdrawals, and other alternatives (Supporting material
 214 S1). We conducted interviews in two languages, Telugu (regional language) and English,
 215 as per the convenience of the stakeholder (the interviewer is proficient in both languages).
 216 Starting with questions common to all stakeholders we fine-tuned the interview to the
 217 type of stakeholder and the information we sought from them. For example, the ques-
 218 tion on stakeholder’s opinion on positive and negative consequences of a possible water
 219 transfer were discussed in terms of water supply perspective for water users and in terms
 220 of the ecological perspective of NGO representatives. Questions related to water demand
 221 changes under land use/cropping pattern change were discussed in detail with water users
 222 and decision makers but not with NGO representatives.

223 **3.3 SHM validation measures and water security indicators**

224 Models can be validated in two ways: outcome validation and structural validation
 225 (Aghaie et al., 2021). With outcome validation one can assess the model results whereas
 226 with structural validation one can assess whether the structure of model agrees with dif-
 227 ferent opinions. As discussed previously, validating SHMs has been difficult due to in-
 228 tangible variables in the model, limited data availability and lack of protocol for SHMs.
 229 Here, we validate the different SHMs using multiple measures. We use outcome valida-
 230 tion for SHM performance, where we use observed historical data on reservoir storage,
 231 groundwater levels, and the ratio of surface water consumption to groundwater abstrac-
 232 tion.

233 We also identify five indicator variables that represent water security in the study
 234 region as well as the extent to which sustainable limits for water use are approached. These
 235 are:

- 236 (i) Blue water withdrawal exceedance (WWE): Following the procedure suggested by
 237 Steffen et al. (2015), we quantifies the limits of blue water use for the Krishna River
 238 at NS. First, the natural inflows to the reservoir are classified into low flow, in-
 239 termediate flow, and high flow months using the variable monthly flow method
 240 (Pastor et al., 2014). We then define blue water withdrawal limits using a conser-
 241 vative estimate of 25%, 40%, and 55% of mean monthly flow for low, intermedi-
 242 ate, and high flow months, respectively. These are the freshwater use boundaries
 243 following guidelines in Steffen et al. (2015). When water withdrawal exceeds the
 244 blue water withdrawal limit, the difference between these two is defined as WWE.
- 245 (ii) Minimum environmental flow (MEF) satisfaction: MEF requirements for instream
 246 ecology are set at 30% of the historical flows as per the recommendations of Smakhtin
 247 (2006). MEF limits are estimated at a daily time step by applying the 30% thresh-
 248 old to mean daily flow value across all years. Then, simulations of water released
 249 downstream of the reservoir are compared against these daily thresholds to iden-
 250 tify whether MEF was satisfied or not. This information is condensed into a re-
 251 liability metric that quantifies the relative number of days in a time horizon MEF
 252 requirements were met.
- 253 (iii) Demand deficits: Demand deficits are estimated as the difference between estimated
 254 water demands and water released for demand satisfaction, aggregated across the
 255 entire time horizon.
- 256 (iv) Downstream releases: Downstream releases are analyzed to ascertain whether ex-
 257 treme inflows may lead to releases causing channel erosion and other damages down-
 258 stream of the reservoir.
- 259 (v) Groundwater levels: the output from the groundwater module is visualized to un-
 260 derstand the trajectory of groundwater levels in the command area of the reser-
 261 voir.

262 4 Results

263 4.1 Stakeholder elicited CLDs and SHMs

264 Semi-structured interviews reveal key interactions that were not included in CLD1.
 265 First, farmers highlighted how groundwater supplements surface water irrigation water
 266 provided by the NS reservoir. Second, reservoir authorities revealed certain rules-of-thumb
 267 that are followed in filling and spilling the reservoir, instead of a demand-based rule. Third,
 268 interviews revealed that there is a governance time scale of 5 years at which major de-
 269 cisions related to reducing demands following water saving techniques or identifying al-
 270 ternative water sources or utilizing reservoir’s dead storage, may be taken for regions un-
 271 dergoing prolonged shortages of water (interviewee X quotes “In case of continuous droughts
 272 the focus should be on decentralized management like farm ponds and rainwater har-
 273 vesting, which takes around 5 years to be implemented. Rainwater Harvesting Theme
 274 Park was constructed in Hyderabad to create awareness on rainwater harvesting and ground-
 275 water recharge.”). On the other hand, interview Y quoted “Based on water availability
 276 in the previous year, we decide the crop area and cropping pattern for the current year.
 277 There are instances where we reduce the crop area by a small amount to account for deficits
 278 of previous year”, indicating that farmers may react to deficits that occur even for a sin-
 279 gle year, albeit with a smaller margin of demand reduction.

280 Using such insights, we develop CLDs 2 and 3 (Figure 4). Instead of adding all the
 281 elicited information into a single updated CLD, we added information methodically to
 282 CLD1 by categorizing the responses from stakeholders resulting in CLD2 and CLD3. This

283 exercise is performed to understand the value of information in a model structure at monthly
 284 timestep. For example, first any obvious omissions to the system, such as unaccounted
 285 groundwater pumping or rules-of-thumb followed by reservoir operators, are included in
 286 CLD2. Next, we include water user behavior changes in the most complex version of the
 287 CLD. Various elements of these CLDs are grouped into different modules, highlighted
 288 using background color in Figure 4. Thus, the groundwater and consumer modules are
 289 added to CLD1 after stakeholder inputs. Each module is then translated into a model
 290 by using adequate equations and parameterizations, these are detailed in Sections 4.1.1
 291 and 4.1.2. Note that while stakeholder inputs were used to develop the CLDs, process
 292 related equations and parameterizations were primarily derived from author’s understand-
 293 ing of qualitative stakeholder inputs. Table 2 lists the process differences between CLDs
 294 1, 2, and 3; Table 3 lists the parameters in the models. After stakeholder elicitation, the
 295 reservoir operations are altered to additionally include a rule of thumb to empty the reser-
 296 voir in by April (SHM2 and SHM3). To this end, we estimate the reservoir storage in
 297 the beginning of December and release one-fourth of that volume every month until April
 298 to empty the reservoir. Also, reservoir is allowed to completely fill in the months of Au-
 299 gust and September to maintain maximum storage of 95% of live capacity.

300 We would like to note that this process will vary depending upon the study area
 301 and nature of stakeholder involvement for each study. However, the main idea is to de-
 302 velop multiple model structures and include stakeholder information in a systematic man-
 303 ner to enable testing using multiple modules.

Table 2. Difference between the CLDs. CLD2 and CLD3 are constructed from CLD1 after incorporating stakeholder inputs.

	CLD1 (author developed)	CLD2 (stakeholder elicited)	CLD3 (stakeholder elicited)
Reservoir module	Release based on water availability in the reservoir	CLD1 along with the goal to empty the reservoir at the end of summer and fill the reservoir in monsoon based on reservoir operator inputs.	Same as CLD2
Command area module	Farmers irrigate as per demands	Farmers irrigate as per demands	Farmers irrigate as per updated demands on adapting to deficits
Consumer module	Farmers demand do not respond to experienced water deficits	Same as CLD1	Farmers adapt to experienced deficits. Two adaptation options are included based on whether the experienced deficits are short-term or long-term
Groundwater module	None included as it is assumed farmers exclusively depend upon reservoir water	Included to simulate conjunctive use of surface and groundwater in the command area as per the inputs from the farmers	Same as CLD2

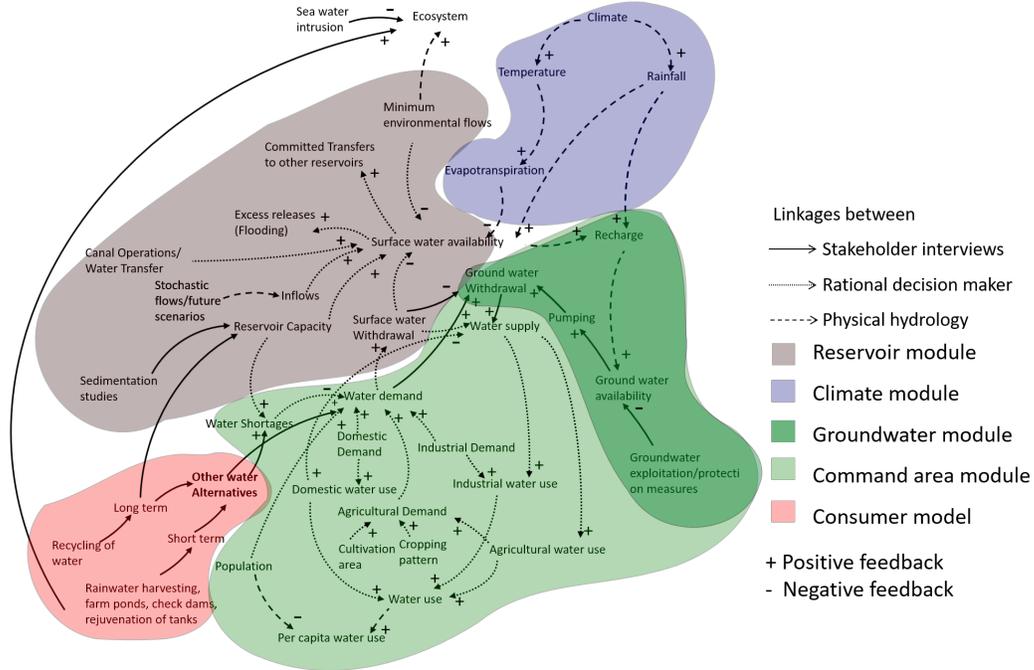


Figure 4. Fully developed stakeholder elicited CLD (CLD 3) for NS reservoir. CLD 2 includes the groundwater module (CLD2 shown in Figure S4 of supporting information). CLD3 additionally includes a consumer water use module. We depict three types of linkages; derived from physical hydrology (dashed lines), from an assumed rational decision maker (dotted lines), and from stakeholder interviews (solid lines). Colors represent different modules of the system - reservoir module is shown in purple, climate module is shown in blue, consumer module is shown in pink, command area module is shown in light green, and groundwater module is shown in dark green. Positive feedbacks are shown by the + sign and negative feedbacks by the - sign.

304

4.1.1 Groundwater module

305

306

307

308

309

310

311

The groundwater heads are simulated assuming the entire command area as a single control volume. We use a lumped parsimonious water balance model that simulates groundwater head as function of rainfall (P_t in m), pumping (Q_{p_t} in m^3) and a lateral outflow term (Equation 2). The model is based on the recent model by Elangovan et al. (2021), which has shown promising application to the urban region of Hyderabad, also serviced by the NS reservoir. Here we include an additional lateral outflow term that allows us to capture the effect of subsurface groundwater fluxes, which are unobservable.

$$h_t = h_{t-1} + \frac{r * (P_t)}{S_y} - \frac{Q_{p_t}}{S_y * A} - \alpha h_{t-1} \quad (2)$$

312

313

314

315

316

317

318

In Equation 2, h_t is the groundwater level at time t in m, r is recharge factor, S_y is specific yield, A is aquifer area in m^2 . r varies between 0 and 1, α determines the lateral flux from the aquifer as a fraction of aquifer head and varies between 0 to 1. Simulated groundwater heads are compared against Theisson-polygon averaged groundwater heads using all the observation wells in the command area. 70% of the data is used for calibration of parameters while the remaining 30% data is used for validation (Table 3). When water released from reservoir fails to satisfy demands, it triggers pump-

319 ing in the command area for SHM2 and SHM3. Pumping volumes are set equal to the
 320 unmet demand and is bounded by 200 Mm³. This is the upper limit of pumping in the
 321 command area based on developed infrastructure (Venot et al., 2007).

322 4.1.2 Consumer Water Use Module

323 The consumer model simulates end user’s water use behavior as elicited from in-
 324 terviews. It adapts demands based on deficits in demand satisfaction in previous years
 325 (Equation 3-4).

$$ad_t = \begin{cases} ad_t & ad_{t-12} = 0 \\ ad_t - \min(ad_{t-12}, \phi) & df_{t-12 \times m} > 0 \quad m = 1 \\ ad_t - \min(2 \times ad_{t-12}, k\phi) & df_{t-12 \times m} > 0 \quad m \in [1, \dots, 5] \end{cases} \quad (3)$$

$$df_t = d_t - ad_t \quad (4)$$

326 In Equation 3-4, ad_t is the actual demand, d_t is the water released for demand sat-
 327 isfaction, and df_t is the deficit at time t , k and ϕ are demand reduction and multiplier
 328 for reduction parameters fixed from literature and earlier studies on India in case of short-
 329 term and long-term deficits. A deficit is classified as long-term when water users face five
 330 consecutive years of water shortages for that month, other deficits are classified as short-
 331 term. In short-term (long-term) deficits, water users reduce their demands equal to (twice
 332 of) the experienced deficit of the prior year, or 62.5 Mm³ (125 Mm³), whichever is smaller.
 333 Here, ϕ is equal to 62.5 and value of k is 2. The upper limits on demand reduction for
 334 long-term deficits are largely consistent with other studies (Bhave et al., 2018; Ashoori
 335 et al., 2017; Nechifor & Winning, 2018). The upper limit for short-term deficits was set
 336 at half that for long-term deficits. In case of long-term deficits, reservoir operator adap-
 337 tation is also considered by increasing the reservoir storage capacity utilizing water from
 338 dead storage. NS reservoir storage capacity of 5,733 Mm³ is increased by 500 Mm³ dur-
 339 ing long-term deficits with a maximum limit of 6840 Mm³.

Table 3. List of parameters in SHMs developed

Parameter	Unit	Description	Module	Data/calibration
r	-	Recharge factor	Command area	Calibrated
Sy	-	Specific yield	Command area	Calibrated
b	m	Maximum depth of groundwater	Command area	Calibrated
α	-	Lateral outflow fraction	Command area	Calibrated
ϕ	Mm ³	Demand reduction value	Consumer water use	Data from literature
k	-	Multiplier for demand reduction	Consumer water use	Data from literature

340 4.2 Calibration and Validation of SHMs

341 4.2.1 Groundwater module

342 We divide the period of available groundwater levels (2007-2013) into a calibration
 343 (2007-2011) and validation (2011-2013) period to estimate four parameters (recharge co-
 344 efficient r , specific yield Sy , lateral outflow fraction α , and maximum depth of ground-
 345 water b) for the groundwater module in SHM2 and SHM3. We calibrate the parame-
 346 ters using the Nondominated Sorting Genetic Algorithm II (NSGA-II, (Deb et al., 2002))

347 that minimizes two objective functions: Nash Sutcliffe Efficiency and mean absolute error.
 348 The calibration is carried out using an open source python toolbox, REGSim tool-
 349 box developed by Elangovan et al. (2021). Two values each of r and α are defined for
 350 monsoon and non-monsoon season following recommendations by Elangovan et al. (2021)
 351 for this region. The pumping volumes are set equal to unmet demand from surface re-
 352 sources and is bounded by 200 Mm³ based on infrastructure available in the region (Venot
 353 et al., 2007). The model attains NSE of 0.76 (0.84) and 0.76 (0.85) for SHM2 and SHM3,
 354 respectively in the validation (calibration) period (Figure S2 in Supporting Information
 355 S1). The optimal parameter value for S_y is 0.048, r is 0.12 (monsoon) and 0.19 (non-monsoon),
 356 α is 0.07 (monsoon) and 0.1 in (non-monsoon) and b is 11.73 m.

357 For the validation period (2007-2011), we find a general agreement on seasonality
 358 and overall year-to-year trends for groundwater with groundwater levels rising during
 359 monsoons (June-July-August-September) due to increased recharge and falling during
 360 the pre-monsoon period (Figure 5a). Dry season fall (January to April) is primarily due
 361 to increased demand triggered by lower water supply from the NS reservoir and low recharge.
 362 Groundwater levels also fall in the post-monsoon months due to high demands for the
 363 Rabi cropping season (October to March). SHM2 and SHM3 tend to under-predict the
 364 groundwater depletion during the dry months from January to June in 2012 and 2013.
 365 These are also periods of low reservoir storages triggers by low inflows, that likely resulted
 366 in over-extraction of groundwater resources and/or non-linear lateral flow dynamics.

367 ***4.2.2 Reservoir storage levels and relative usage of surface and ground-*** 368 ***water for irrigation***

369 When comparing reservoir storage observations (2000-2013) against simulated, we
 370 note a correlation coefficient (Pearson) between observed and simulated monthly stor-
 371 age values are 0.57, 0.85 and 0.87 for SHM1, SHM2, and SHM3, respectively (Figure 5b).
 372 We note a strong improvement in model performance when information on reservoir oper-
 373 ation obtained from elicitation is included (SHM2 and SHM3). A substantial decrease
 374 in storage during the multi-year drought of 2002-2004 is observed across all SHMs (Venot,
 375 Reddy, & Umamathy, 2010). SHM2 and SHM3 simulations show substantial difference
 376 in simulated peak storage values post 2004 because the consumer water use module in
 377 SHM3 lowers demands following the drought, resulting in greater storage values. Inci-
 378 dentally, these higher values are more in agreement with observations, even in the val-
 379 idation period.

380 We also compare ability of SHMs to capture relative contributions of groundwa-
 381 ter and surface water by simulating the ratio of respective volumes utilized for irriga-
 382 tion and comparing with observations (Figure 5c). The observed values of ratio of area
 383 under irrigation from surface water to groundwater in the NS command area for 2001-
 384 2002, 2002-2003 and 2005-2006, are 1.03, 0.12, and 3.56, respectively (Venot, Reddy, &
 385 Umamathy, 2010). The corresponding ratio of simulated values for volume of water uti-
 386 lized from surface water to groundwater for SHM2 (SHM3) are 6.08 (6.08), 3.02 (3.02),
 387 26.07 (24.82), respectively. Both SHM2 and SHM3 demonstrate the ability to simulate
 388 the observed reduction in the ratio of surface water to groundwater for 2001-2002 and
 389 2002-2003. Also, an increase in the utilization ratio was noted for both SHM2 and SHM3
 390 when comparing 2002-2003 with 2005-2006, which is consistent with observations. These
 391 trends are also meaningful considering that 2002-2003 was a drought year, thus more re-
 392 liance on groundwater is expected for 2002-2003 resulting in lower ratios. Note that the
 393 absolute values are different due to incommensurable variables used in the ratio estima-
 394 tion, i.e., volume for simulated data and area for the observed data.

4.2.3 *Water security for environment and human well-being*

We now compare the inferred water and ecological security states of the NS reservoir and its command area across the three model structures for the simulation period 1968-2013 (Figure 6). Demands increase significantly with time, mainly during 1968-1982 and are stabilized by year 1983 (Supplementary Figure S3). So, this time period is divided into pre- and post-demand stabilization for the years 1968-1982 and 1983-2013 respectively.

The mean annual volumes of water withdrawal exceedances (WWE) for SHM1, SHM2, and SHM3 are 5.21 Bm^3 , 6.34 Bm^3 , and 6.29 Bm^3 , respectively (Figure 6a). This implies that the limits of sustainable blue (surface) water withdrawals are exceeded more frequently and by a greater magnitude by SHM2 and SHM3 where a rule to empty the reservoir at the end of summer and fill the reservoir in monsoon is followed by the reservoir operators. These exceedances are observed in the monsoon season for SHM2 and SHM3, where water is extracted to store in the reservoir. Whereas, in the case of SHM1, water is released downstream based on water availability, which is proportional to the natural flows reducing the water withdrawal exceedance. WWE for SHM1 is high during post-demand stabilization (5.96 Bm^3) compared to pre-demand stabilization (3.71 Bm^3) due to increase in demands and thereby increase in water withdrawal for demand satisfaction. Furthermore, WWE are high for SHM1 compared to SHM2 and SHM3 during the drought period (2001-2002), with values of 3.86 Bm^3 (2.59 Bm^3 , 2.59 Bm^3) for SHM1 (SHM2, SHM3). This is due to the role played by conjunctive use of surface water and groundwater for SHM2 and SHM3, whereas demand satisfaction for SHM1 solely depends on the surface water withdrawal, exceeding the withdrawal limits.

We find substantial differences in inferred water demand deficits across the three model structures. SHM3 that incorporates adaptive behavior of water users results in mean annual deficits of 0.69 Bm^3 . SHM2 that does not incorporate such adaptation results in greater deficit volume of 0.72 Bm^3 when compared to SHM3. Deficits are not observed for SHM1 except during drought periods (mean annual deficit of 0.28 Bm^3) due to its nature of operation of reservoirs to satisfy demands based on water availability. We see continuously increasing demand deficits in the historical period of NS reservoir due to increase in water demands and reduced water availability in the reservoir accounted by rapid upstream developments (Figure 6 c). Deficit during pre-demand stabilization period is zero for all SHM structures; 1.09 Bm^3 (1.04 Bm^3) for SHM2 (SHM3) during the post-demand stabilization period. These deficits increase by 86% during the drought period (2001-2002) with annual deficit of 2.03 Bm^3 (1.94 Bm^3) for SHM2 (SHM3). This suggests that demand deficits increase irrespective of model structure with SHM3 resulting in less deficit compared to SHM2.

Groundwater levels are observed to be the same for both SHM2 (annual mean depth of 6.47 m) and SHM3 (annual mean depth of 6.48 m) except with a small variation during the post drought years of 2004-2006 (Figure 6b). Mean annual depth of groundwater level is the same in pre-demand stabilization period for SHM2 and SHM3 with depth of 6.63 m, which reduces in the post-drought stabilization to 6.38 m (6.4 m) for SHM2 (SHM3). This shows reduced groundwater levels with increase in demands and higher level for SHM3 compared to SHM2 due to consumer adaptation. Also, groundwater abstraction is slightly higher for SHM2 during post drought period (5.91 m and 5.95 m for SHM2 and SHM3 for years 2004-2006) due the compound effect of increasing demands in the command area of the NS reservoir and not adapting to changes in water availability. We find a significant role of the consumer module that updates demand based on perceived long-term deficits in SHM3 but not in SHM2 when comparing groundwater levels. Between 2001 and 2005 (drought and post-drought periods), we observe a considerable difference in water demands. This is a period of reduced inflows, where the adaptation behavior of consumers to reduce demands becomes apparent. These lower demands in turn result in lower deficits, leading to reduced groundwater abstractions (Figure S5).

Thus, overall SHM3 suggests higher groundwater levels when compared to SHM2. The difference in average annual demands between SHM2 and SHM3 is 429 Mm³, which translates to a difference in deficits of 152 Mm³. Groundwater restores rapidly for SHM3 compared to SHM2 with a maximum difference in depth of 0.2 m (20 mm) occurring in February 2004, which is a 5% improvement for SHM3 compared to SHM2.

We track downstream releases from NS reservoir for future flood occurrences that may lead to socio-economic damages to populations residing downstream as well as ecological damages from changes in channel geomorphology (Figure 6d). We find that a few instances of high flow releases across different SHMs. However, the differences between SHM model structures are negligible for this variable. We find a significant reduction in downstream releases for post-demand stabilization period (12 Bm³) compared to pre-demand stabilization (23 Bm³). So, downstream releases reduce with time with lowest during the drought period (1.89 Bm³). The NS reservoir fails to satisfy minimum environmental flows (MEF) irrespective of model structures (Figure 6e). However, SHM1 generally yields lower MEF values than SHM2 and SHM3. Historical mean annual MEF for SHM3 (SHM2) is 0.50 (0.52) suggesting that socio-economic development in the command area could adversely affect downstream flows. Satisfaction of minimum environmental flow reliability also reduces with time (reliability of 0.56 and 0.47 in pre- and post-demand stabilization period respectively for SHM3), performing worse during the drought period (reliability of 0.21 for SHM3). Increase in deficits are consistent with low releases downstream and reduced reliability of satisfaction of MEF.

5 Discussion

We evaluate multiple structures of SHMs as an initial attempt to illustrate the uncertainties associated with conceptual model development and model structure. The command area of the recipient basin is predominantly cultivated by small and marginal farmers (Figure S1 in Supporting Information S1), where marginal farmers cultivate up to one hectare, and small-scale farmers cultivate between one and two hectares. The different CLDs and SHMs in this study do not always capture the different priorities of different farmers, nor the range of different demand reduction methods that may apply for different sizes of land holdings. For instance, farm ponds may be applicable for larger land holdings while farmers with smaller land holdings may depend on the canal-based surface water supply. We also assume a uniform aquifer, which is a necessary simplification, but may mean that heterogeneity in groundwater availability and extraction, and its implications may not have been sufficiently captured. Few issues identified by stakeholders in the CLDs, such as seawater intrusion, are not quantified in the SHM, because given the physiographical location of the study region, these impacts are considered relatively less important. These limitations illustrate a key issue with modelling human-water interactions, which is that all interactions and feedbacks may not be captured in the CLDs and SHMs. Exploration of the parametric uncertainty associated with the SHM, sediment assessment, and potential impacts of alternative short-term and long-term water management measures are beyond the scope of this study, but could be explored in future studies.

Explicit and implicit choices associated with system boundaries also have implications. For instance, while stakeholders could provide much information about the NS reservoir and command areas, insights regarding interventions outside basin could influence the system are not captured. These include the proposed Polavaram Vijayawada link to transfer water from the Godavari basin to the Krishna basin, and potential upstream changes in irrigation demand through interventions like the Kaleswaram project. Such large scale interventions could affect water availability and demand dynamics besides complex interactions with exogenous factors like climate change, along with uncertainties associated with their future management.

499 We find that long drought has substantial impact on the systems model. In case
500 of low inflows, releasing for demand satisfaction instead of storing water in the reservoir
501 may worsen the impact of drought, suggesting the need for reservoir operators to proac-
502 tively manage reservoir storage to satisfy water demand. However, capturing reservoir
503 operator behaviour is difficult. For instance, during the drought period of 2002-2004 (Fig-
504 ure 5), though the operator did not get sufficient inflows to raise the reservoir storage,
505 they chose to release water through the canals which the SHM model developed does not
506 capture, and warrants more research. This drought also reveals profound changes in the
507 system resulting in equifinality between adaptation of reservoir operators and water users.
508 Both adapt dynamically and isolating their individual impacts within a complex system
509 is challenging. Increase in storage levels post-drought could be due to lower demands (adap-
510 tation by water users) or risk-averse behavior of the operator. Adaptation by water users
511 (farmers) is considered by reduction of demands and also found in earlier studies (Venot,
512 Reddy, & Umamathy, 2010; Venot, Jella, et al., 2010; Molle et al., 2010; Kakumanu et
513 al., 2019). Adaptation of reservoir operators is hard to quantify as their adaptation be-
514 havior is not explicitly characterized. However, in SHM3, we consider farmer adapta-
515 tion by reduction of demands and a logical reservoir operator adaptation by increasing
516 the water stored in the reservoir (utilizing small amount of water from dead storage) which
517 resulted in a good validation of post-drought water availability. Such adaptation of reser-
518 voir operator is not included in the literature. Stakeholders involved in reservoir oper-
519 ation did not explicitly reveal adaptation, but suggested the need to adapt policies dur-
520 ing post-drought periods and included as part of structural modification. Information
521 on unpredictable, complex behavior of reservoir operators, and legislative policies on ac-
522 tions during drought period were not established during elicitation. Overall, more de-
523 tailed analysis on multiple working hypothesis are needed on how humans respond to
524 prolonged droughts.

525 One key concern associated with irrigation water demand change is the effect on
526 downstream water availability, especially for riparian ecosystems. SHMs tools provide
527 more value when stakeholder inputs are used to identify the linkages, linkages and feed-
528 backs (O’Keeffe et al., 2018). In our discussions stakeholders identified better observa-
529 tion networks, remotely sensed information, and constant monitoring of water-related
530 parameters, especially streamflow and water distribution through canals, for better un-
531 derstanding of the system. For instance, canal water may not always reach the tail-end
532 of the command area, sometimes due to over extraction by users in head or middle reaches,
533 for which better observations would be useful. Also, complex quantitative and qualita-
534 tive information available anecdotally, from newspapers and interactions with stakehold-
535 ers could provide useful insights. Stronger two-way flow of information between mod-
536 elers and stakeholders could help include and assess a wider range of issues, and help de-
537 velop management systems that support greater equity in the distribution of water, en-
538 hanced protection of riparian ecosystems, and wider societal goals.

539 6 Conclusion

540 In this study, we develop socio-hydrologic models for large scale reservoirs in irri-
541 gation dominated command areas of a major multi-purpose water resources project. There
542 are several unique features of this setting: 1) the conjunctive use of surface and ground-
543 water in the command areas of the reservoirs, 2) the lack of standard norms for reser-
544 voir operations beyond existing government regulations on prioritization of water releases,
545 and 3) hydroclimatic variability of the Indian summer monsoon that may result in multi-
546 year droughts triggering demand adaptation behavior in farmers. The project and its
547 overall setting are indicative of several such projects in developing countries. We have
548 attempted to capture the feedbacks between water availability and water use using the
549 method of semi-structured interviews. Our results highlight the value of including de-
550 mand adaptation behavior by farmers in reservoir operation models to accurately un-

551 derstand the water security conditions in the project’s command area in the aftermath
552 of multi-year droughts. We also show that model outputs can be sensitive to varying lev-
553 els of stakeholder inputs, and highlight the importance of independent validation of socio-
554 hydrological models.

555 This study provides a useful methodological framework for understanding how to
556 consider, conceptualize, characterize, and assess different aspects of human-water inter-
557 actions to support better management of water resources in the future. The application
558 of the model provides a significant planning and management avenue for exploring dif-
559 ferent model structure for the historical period with a possibility to analyze for future
560 changes in climate and socio-economic conditions. We show why it is necessary to de-
561 velop SHMs of different levels of complexity and with different inputs, project the sys-
562 tem’s state at larger scales, and explore uncertainties in human-water interactions.

563 One of the crucial facets of this study is stakeholder elicitation, where we include
564 the attitudes and preferences of the stakeholder in the SHM framework using three dif-
565 ferent formulations of the CLD. We find better performance of the SHM which includes
566 stakeholder information in terms of annual demand deficits for different structures of SHM.
567 We propose and use a methodology for the development of the structure of socio-hydrological
568 models from quantitative data and their validation with the available observed ground
569 data. Overall, the dynamics of the system’s state variables are impacted by the vary-
570 ing inputs from stakeholders about the complex interactions, and the consequent rep-
571 resentation in the models. Further research may include using the developed SHMs to
572 explore further interactions of this system with upstream regions and with neighboring
573 basins, assessing adaptive behavior of water users under a wider range of climate change
574 projections, and assessing the impact of different structures of SHMs.

575 **7 Open Research**

576 The hydrological data is obtained from Srivastava et al. (2009); Pai et al. (2014).
577 The land use data is obtained from Roy et al. (2016). Data and codes to reproduce the
578 results are uploaded to a GitHub repository (<https://github.com/ssaiveena/shm.git>) (Sunkara,
579 2023).

580 **Acknowledgments**

581 Sai Veena and Riddhi Singh are funded by DST-SERB early career research award num-
582 ber ECR/2015/000355. The authors thank the Central Water Commission (CWC) and
583 the Irrigation and CAD Department, Telangana, for providing the data. Ajay Bhave is
584 funded by the Water Security and Sustainable Development Hub funded by the UK Re-
585 search and Innovation’s Global Challenges Research Fund (GCRF) [Grant No. ES/S008179/1].

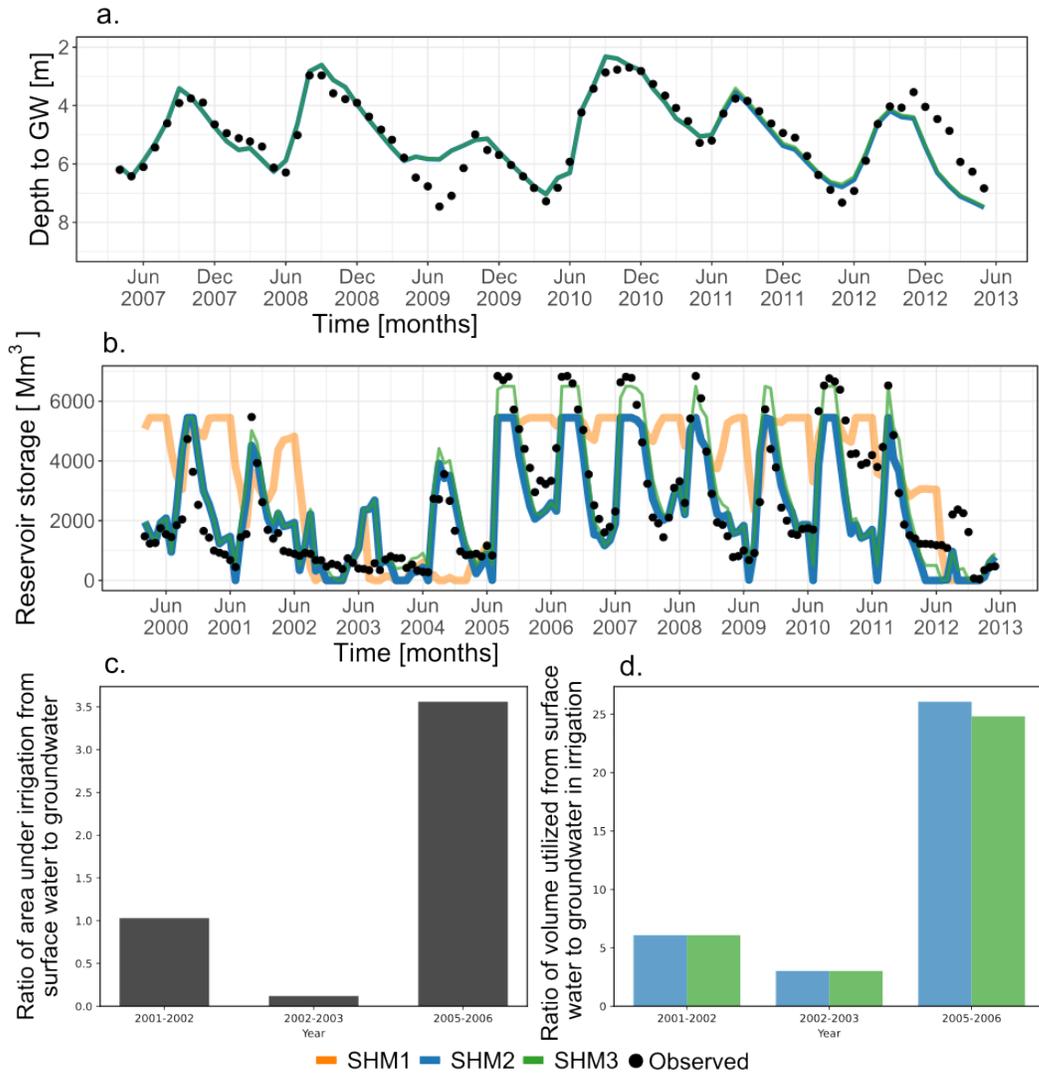


Figure 5. (a) Depth to groundwater in the command area of the NS reservoir for the calibration (2007-2011) and validation (2011-2013) periods as simulated by SHM2, and SHM3. Calibration is used to identify five groundwater process parameters: two seasonal recharge coefficients, specific yield, two coefficients for lateral flux, and depth to bedrock. (b) Monthly live storage [Mm³] in the NS reservoir for 2000-2013 as simulated by SHM1, SHM2, and SHM3. Observed values are shown by black circles while simulations are shown by solid colored lines. (c) Ratio of surface to groundwater utilized. Here, observed data is the ratio of areas whereas for SHM data is ratio volume of water utilized.

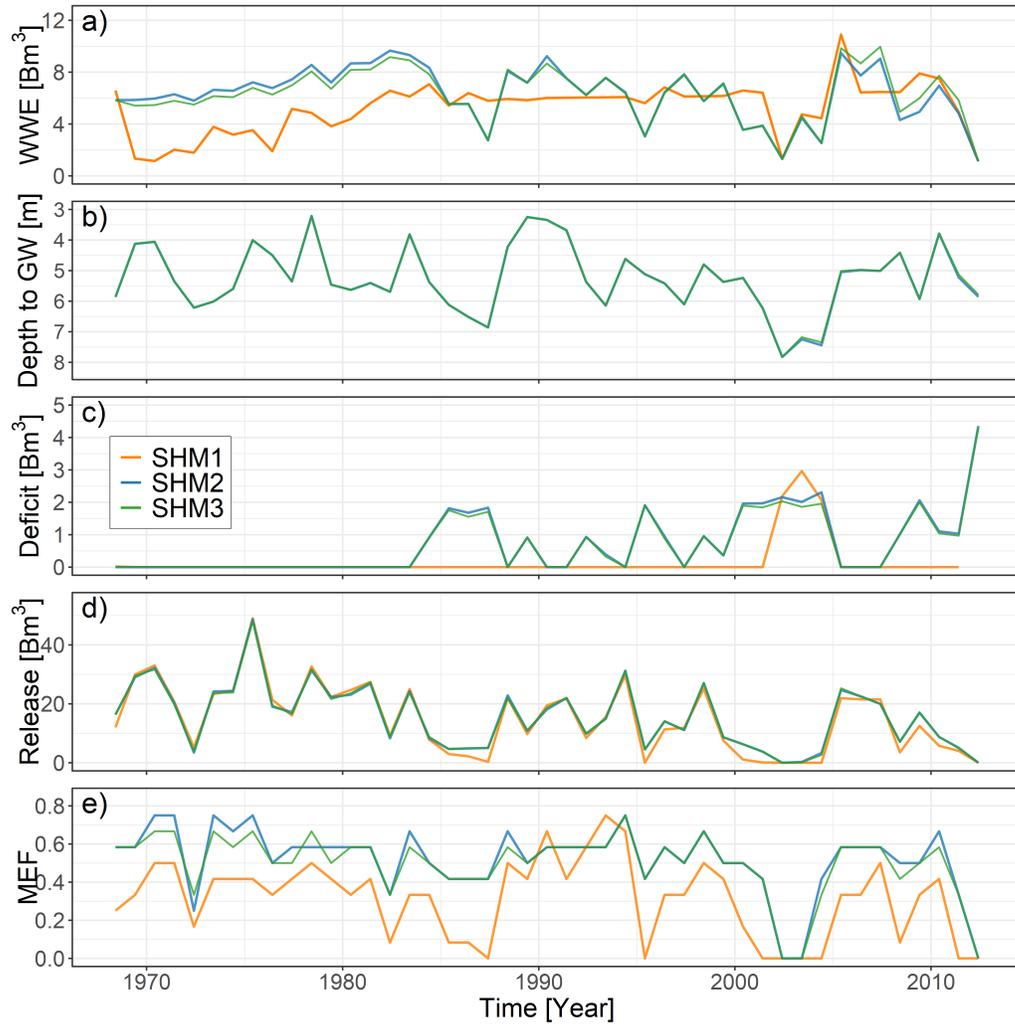


Figure 6. Historical (1968-2013) values of annual a) water withdrawal exceedance (WWE, Bm^3), b) Depth to groundwater [m], c) demand deficits [Bm^3], d) reservoir downstream releases [Bm^3], and e) satisfaction of minimum environmental flows (MEF) for the NS reservoir.

References

586

587

588

589

590

591

592

593

594

595

596

597

598

599

600

601

602

603

604

605

606

607

608

609

610

611

612

613

614

615

616

617

618

619

620

621

622

623

624

625

626

627

628

629

630

631

632

633

634

635

636

637

638

639

- Aghaie, V., Afshar, A., & Alizadeh, H. (2021). Socio-hydrological agent-based modelling for analysing the impacts of supply enhancement strategies on the cap-and-trade scheme. *Hydrological Sciences Journal*, *66*(4), 555–564.
- Ashoori, N., Dzombak, D. A., & Small, M. J. (2017). Identifying water price and population criteria for meeting future urban water demand targets. *Journal of Hydrology*, *555*, 547–556.
- Bhave, A. G., Bulcock, L., Dessai, S., Conway, D., Jewitt, G., Dougill, A. J., ... Mkwambisi, D. (2020). Lake malawi's threshold behaviour: a stakeholder-informed model to simulate sensitivity to climate change. *Journal of Hydrology*, *584*, 124671.
- Bhave, A. G., Conway, D., Dessai, S., & Stainforth, D. A. (2018). Water resource planning under future climate and socioeconomic uncertainty in the cauvery river basin in karnataka, india. *Water resources research*, *54*(2), 708–728.
- Biggs, T., Gaur, A., Scott, C., Thenkabail, P., Gangadhara Rao, P., Gumma, M. K., ... Turrall, H. (2007). *Closing of the krishna basin: Irrigation, streamflow depletion and macroscale hydrology* (Vol. 111). IWMI.
- Blair, C., Gralla, E., Wetmore, F., Goentzel, J., & Peters, M. (2021). A systems framework for international development: The data-layered causal loop diagram. *Production and Operations Management*, *30*(12), 4374–4395.
- Cai, X., Marston, L., & Ge, Y. (2015). Decision support for integrated river basin management—scientific research challenges. *Science China Earth Sciences*, *58*(1), 16–24.
- Chen, X., Wang, D., Tian, F., & Sivapalan, M. (2016). From channelization to restoration: Sociohydrologic modeling with changing community preferences in the kissimmee river basin, florida. *Water Resources Research*, *52*(2), 1227–1244.
- Daniel, D., Prawira, J., Djono, A., Pamudji, T., Subandriyo, S., Rezagama, A., & Purwanto, A. (2021). A system dynamics model of the community-based rural drinking water supply program (pamsimas) in indonesia. *Water*, *13*(4), 507.
- Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, *6*(2), 182–197.
- Di Baldassarre, G., Mazzoleni, M., & Rusca, M. (2021). The legacy of large dams in the united states. *Ambio*, 1–11.
- Di Baldassarre, G., Sivapalan, M., Rusca, M., Cudennec, C., Garcia, M., Kreibich, H., ... others (2019). Sociohydrology: scientific challenges in addressing the sustainable development goals. *Water Resources Research*, *55*(8), 6327–6355.
- Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., & Blöschl, G. (2015). Debates—perspectives on socio-hydrology: Capturing feedbacks between physical and social processes. *Water Resources Research*, *51*(6), 4770–4781.
- Du, E., Tian, Y., Cai, X., Zheng, Y., Li, X., & Zheng, C. (2020). Exploring spatial heterogeneity and temporal dynamics of human-hydrological interactions in large river basins with intensive agriculture: A tightly coupled, fully integrated modeling approach. *Journal of Hydrology*, *591*, 125313.
- Elangovan, L., Singh, R., & Kambhammettu, B. (2021). Regsim: An open-source framework to estimate recharge and simulate groundwater heads. *Computers & Geosciences*, *157*, 104921.
- Elshafei, Y., Coletti, J., Sivapalan, M., & Hipsey, M. (2015). A model of the sociohydrologic dynamics in a semiarid catchment: Isolating feedbacks in the coupled human-hydrology system. *Water Resources Research*, *51*(8), 6442–6471.
- Elshafei, Y., Sivapalan, M., Tonts, M., & Hipsey, M. (2014). A prototype framework for models of socio-hydrology: identification of key feedback loops and

- parameterisation approach. *Hydrology and Earth System Sciences*, 18(6), 2141–2166.
- EPTRI. (2008). Integrated social and environmental assessment study for complete rehabilitation and modernization of nagarjunasagar project. *Hyderabad, India*.
- Foster, T., Brozović, N., & Butler, A. P. (2014). Modeling irrigation behavior in groundwater systems. *Water resources research*, 50(8), 6370–6389.
- Gaur, A., Biggs, T. W., Gumma, M. K., Parthasaradhi, G., & Turrall, H. (2008). Water scarcity effects on equitable water distribution and land use in a major irrigation project—case study in india. *Journal of irrigation and Drainage Engineering*, 134(1), 26–35.
- Ghoreishi, M., Razavi, S., & Elshorbagy, A. (2021). Understanding human adaptation to drought: agent-based agricultural water demand modeling in the bow river basin, canada. *Hydrological Sciences Journal*, 66(3), 389–407.
- Giordano, R., Brugnach, M., & Pluchinotta, I. (2017). Ambiguity in problem framing as a barrier to collective actions: some hints from groundwater protection policy in the apulia region. *Group Decision and Negotiation*, 26(5), 911–932.
- Gohari, A., Eslamian, S., Mirchi, A., Abedi-Koupaei, J., Bavani, A. M., & Madani, K. (2013). Water transfer as a solution to water shortage: a fix that can backfire. *Journal of Hydrology*, 491, 23–39.
- Halbe, J., Pahl-Wostl, C., & Adamowski, J. (2018). A methodological framework to support the initiation, design and institutionalization of participatory modeling processes in water resources management. *Journal of Hydrology*, 556, 701–716.
- Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Applied engineering in agriculture*, 1(2), 96–99.
- Herrera-Franco, G., Montalván-Burbano, N., Carrión-Mero, P., & Bravo-Montero, L. (2021). Worldwide research on socio-hydrology: A bibliometric analysis. *Water*, 13(9), 1283.
- Inam, A., Adamowski, J., Prasher, S., Halbe, J., Malard, J., & Albano, R. (2017). Coupling of a distributed stakeholder-built system dynamics socio-economic model with sahsmod for sustainable soil salinity management—part 1: Model development. *Journal of Hydrology*, 551, 596–618.
- Jacobs, M. H., & Buijs, A. E. (2011). Understanding stakeholders’ attitudes toward water management interventions: Role of place meanings. *Water Resources Research*, 47(1).
- Jones, B., & O’Neill, B. C. (2016). Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environmental Research Letters*, 11(8), 084003.
- Kakumanu, K. R., Kaluvai, Y. R., Balasubramanian, M., Nagothu, U. S., Kotapati, G. R., & Karanam, S. (2019). Adaptation to climate change: impact of capacity building, india. *Irrigation and Drainage*, 68(1), 50–58.
- Kandasamy, J., Sountharajah, D., Sivabalan, P., Chanan, A., Vigneswaran, S., & Sivapalan, M. (2014). Socio-hydrologic drivers of the pendulum swing between agricultural development and environmental health: a case study from murrumbidgee river basin, australia. *Hydrology and Earth System Sciences*, 18(3), 1027–1041.
- Khadim, F. K., Bagtzoglou, A. C., Dokou, Z., & Anagnostou, E. (2023). A socio-hydrological investigation with groundwater models to assess farmer’s perception on water management fairness. *Journal of Hydrology*, 620, 129481.
- Kwak, Y., Deal, B., & Mosey, G. (2021). Landscape design toward urban resilience: Bridging science and physical design coupling sociohydrological modeling and design process. *Sustainability*, 13(9), 4666.
- Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., . . . others (2011). High-resolution mapping of the world’s reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the*

- 695 *Environment*, 9(9), 494–502.
- 696 Li, D., Zhao, J., & Govindaraju, R. S. (2019). Water benefits sharing under trans-
697 boundary cooperation in the Lancang-Mekong river basin. *Journal of Hydrology*,
698 577, 123989.
- 699 Li, R., Guo, P., & Li, J. (2018). Regional water use structure optimization under
700 multiple uncertainties based on water resources vulnerability analysis. *Water*
701 *resources management*, 32(5), 1827–1847.
- 702 Li, X., Cheng, G., Lin, H., Cai, X., Fang, M., Ge, Y., . . . Li, W. (2018). Water-
703 shed system model: The essentials to model complex human-nature system at
704 the river basin scale. *Journal of Geophysical Research: Atmospheres*, 123(6),
705 3019–3034.
- 706 Mbavarira, T. M., & Grimm, C. (2021). A systemic view on circular economy in the
707 water industry: Learnings from a Belgian and Dutch case. *Sustainability*, 13(6),
708 3313.
- 709 Merz, L., Yang, D., & Hull, V. (2020). A metacoupling framework for exploring
710 transboundary watershed management. *Sustainability*, 12(5), 1879.
- 711 Molle, F., Wester, P., & Hirsch, P. (2010). River basin closure: Processes, implica-
712 tions and responses. *Agricultural Water Management*, 97(4), 569–577.
- 713 Müller, M. F., & Levy, M. C. (2019). Complementary vantage points: Integrating
714 hydrology and economics for sociohydrologic knowledge generation. *Water Re-*
715 *sources Research*, 55(4), 2549–2571.
- 716 Nechifor, V., & Winning, M. (2018). Global economic and food security impacts
717 of demand-driven water scarcity-alternative water management options for a
718 thirsty world. *Water*, 10(10), 1442.
- 719 Noël, P. H., & Cai, X. (2017). On the role of individuals in models of coupled hu-
720 man and natural systems: Lessons from a case study in the Republican river
721 basin. *Environmental Modelling & Software*, 92, 1–16.
- 722 Nordhaus, W., & Chen, X. (2016). Global gridded geographically based economic
723 data (g-econ), version 4. *NASA Socioeconomic Data and Applications Center*
724 *(SEDAC)*.
- 725 NWDA. (2021). National water development agency, feasibility studies. *Accessed*
726 *January 21*.
- 727 O’Keeffe, J., Moulds, S., Bergin, E., Brozović, N., Mijic, A., & Buytaert, W. (2018).
728 Including farmer irrigation behavior in a sociohydrological modeling framework
729 with application in north India. *Water Resources Research*, 54(7), 4849–4866.
- 730 Pai, D., Rajeevan, M., Sreejith, O., Mukhopadhyay, B., & Satbha, N. (2014). *Devel-*
731 *opment of a new high spatial resolution (0.25° × 0.25°) long period (1901–2010)*
732 *daily gridded rainfall data set over India and its comparison with existing data*
733 *sets over the region* [dataset].
- 734 Pande, S., & Savenije, H. H. (2016). A sociohydrological model for smallholder farm-
735 ers in Maharashtra, India. *Water Resources Research*, 52(3), 1923–1947.
- 736 Purwanto, A., Sušnik, J., Suryadi, F., & de Fraiture, C. (2019). Using group model
737 building to develop a causal loop mapping of the water-energy-food security
738 nexus in Karawang regency, Indonesia. *Journal of Cleaner Production*, 240,
739 118170.
- 740 Purwanto, A., Sušnik, J., Suryadi, F., & de Fraiture, C. (2021). Quantitative simu-
741 lation of the water-energy-food (WEF) security nexus in a local planning context
742 in Indonesia. *Sustainable Production and Consumption*, 25, 198–216.
- 743 Ram, S. A., & Irfan, Z. B. (2021). Application of system thinking causal loop mod-
744 elling in understanding water crisis in India: A case for sustainable integrated
745 water resources management across sectors. *HydroResearch*, 4, 1–10.
- 746 Roobavannan, M., Kandasamy, J., Pande, S., Vigneswaran, S., & Sivapalan, M.
747 (2017). Role of sectoral transformation in the evolution of water management
748 norms in agricultural catchments: A sociohydrologic modeling analysis. *Water*
749 *Resources Research*, 53(10), 8344–8365.

- 750 Ross, A. R., & Chang, H. (2021). Modeling the system dynamics of irrigators' re-
 751 siliance to climate change in a glacier-influenced watershed. *Hydrological Sci-*
 752 *ences Journal*, *66*(12), 1743–1757.
- 753 Roy, P., Meiyappan, P., Joshi, P., Kale, M., Srivastav, V., Srivasatava, S., . . . others
 754 (2016). *Decadal land use and land cover classifications across india, 1985,*
 755 *1995, 2005* [dataset].
- 756 Simonovic, S. (2009). *Managing water resources: Methods and tools for a systems*
 757 *approach (pp. 576)*. Paris.
- 758 Sivapalan, M., Savenije, H. H., Blöschl, G., et al. (2012). Socio-hydrology: A new
 759 science of people and water. *Hydrol. Process*, *26*(8), 1270–1276.
- 760 Srivastava, A., Rajeevan, M., & Kshirsagar, S. (2009). *Development of a high res-*
 761 *olution daily gridded temperature data set (1969–2005) for the indian region*
 762 [dataset]. Wiley Online Library.
- 763 Sterman, J. (2000). *Business dynamics*. McGraw-Hill, Inc.
- 764 Sung, K., Jeong, H., Sangwan, N., & Yu, D. J. (2018). Effects of flood control strate-
 765 gies on flood resilience under sociohydrological disturbances. *Water Resources*
 766 *Research*, *54*(4), 2661–2680.
- 767 Sunkara, S. V. (2023). *Shm* [Software]. Zenodo. Retrieved from [https://doi.org/](https://doi.org/10.5281/zenodo.8388004)
 768 [10.5281/zenodo.8388004](https://doi.org/10.5281/zenodo.8388004) doi: 10.5281/zenodo.8388004
- 769 Troy, T. J., Pavao-Zuckerman, M., & Evans, T. P. (2015). Debates—perspectives on
 770 socio-hydrology: Socio-hydrologic modeling: Tradeoffs, hypothesis testing, and
 771 validation. *Water Resources Research*, *51*(6), 4806–4814.
- 772 Van Emmerik, T., Li, Z., Sivapalan, M., Pande, S., Kandasamy, J., Savenije, H., . . .
 773 Vigneswaran, S. (2014). Socio-hydrologic modeling to understand and mediate
 774 the competition for water between agriculture development and environmental
 775 health: Murrumbidgee river basin, australia. *Hydrology and Earth System*
 776 *Sciences*, *18*(10), 4239–4259.
- 777 Van Rooijen, D. J., Turrall, H., & Wade Biggs, T. (2005). Sponge city: water bal-
 778 ance of mega-city water use and wastewater use in hyderabad, india. *Irrigation*
 779 *and Drainage: The journal of the International Commission on Irrigation and*
 780 *Drainage*, *54*(S1), S81–S91.
- 781 Veena, S., Singh, R., Gold, D., Reed, P., & Bhave, A. (2021). Improving
 782 information-based coordinated operations in interbasin water transfer
 783 megaprojects: Case study in southern india. *Journal of Water Resources*
 784 *Planning and Management*, *147*(11), 04021075.
- 785 Venot, J.-P., Jella, K., Bharati, L., George, B., Biggs, T., Rao, P. G., . . . Acharya,
 786 S. (2010). Farmers' adaptation and regional land-use changes in irrigation
 787 systems under fluctuating water supply, south india. *Journal of Irrigation and*
 788 *Drainage Engineering*, *136*(9), 595–609.
- 789 Venot, J.-P., Reddy, V. R., & Umopathy, D. (2010). Coping with drought in irri-
 790 gated south india: Farmers' adjustments in nagarjuna sagar. *Agricultural Wa-*
 791 *ter Management*, *97*(10), 1434–1442.
- 792 Venot, J.-P., Turrall, H., Samad, M., & Molle, F. (2007). *Shifting waterscapes:*
 793 *explaining basin closure in the lower krishna basin, south india* (Vol. 121).
 794 IWMI.
- 795 Voegeli, G., & Finger, D. C. (2021). Disputed dams: Mapping the divergent stake-
 796 holder perspectives, expectations, and concerns over hydropower development
 797 in iceland and switzerland. *Energy Research & Social Science*, *72*, 101872.
- 798 Wei, J., Wei, Y., & Western, A. (2017). Evolution of the societal value of water
 799 resources for economic development versus environmental sustainability in
 800 australia from 1843 to 2011. *Global Environmental Change*, *42*, 82–92.
- 801 Wescoat Jr, J. L., Siddiqi, A., & Muhammad, A. (2018). Socio-hydrology of chan-
 802 nel flows in complex river basins: Rivers, canals, and distributaries in punjab,
 803 pakistan. *Water Resources Research*, *54*(1), 464–479.
- 804 Wine, M. L. (2020). Climatization of environmental degradation: A widespread

805 challenge to the integrity of earth science. *Hydrological Sciences Journal*,
806 *65*(6), 867–883.
807 Yu, D. J., Chang, H., Davis, T. T., Hillis, V., Marston, L. T., Oh, W. S., . . . War-
808 ing, T. M. (2020). Socio-hydrology: an interplay of design and self-organization
809 in a multilevel world. *Ecology and Society*.

Figure 1.

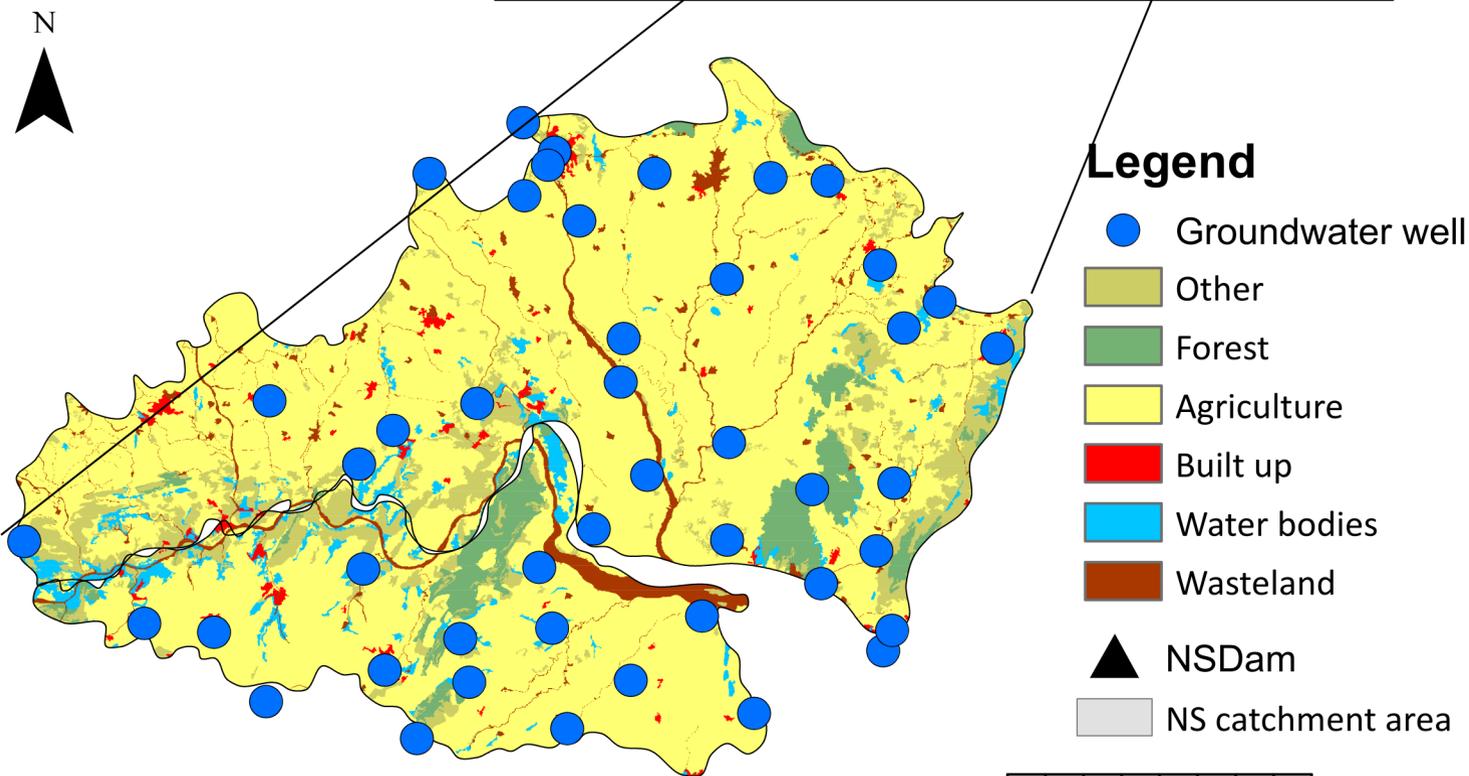
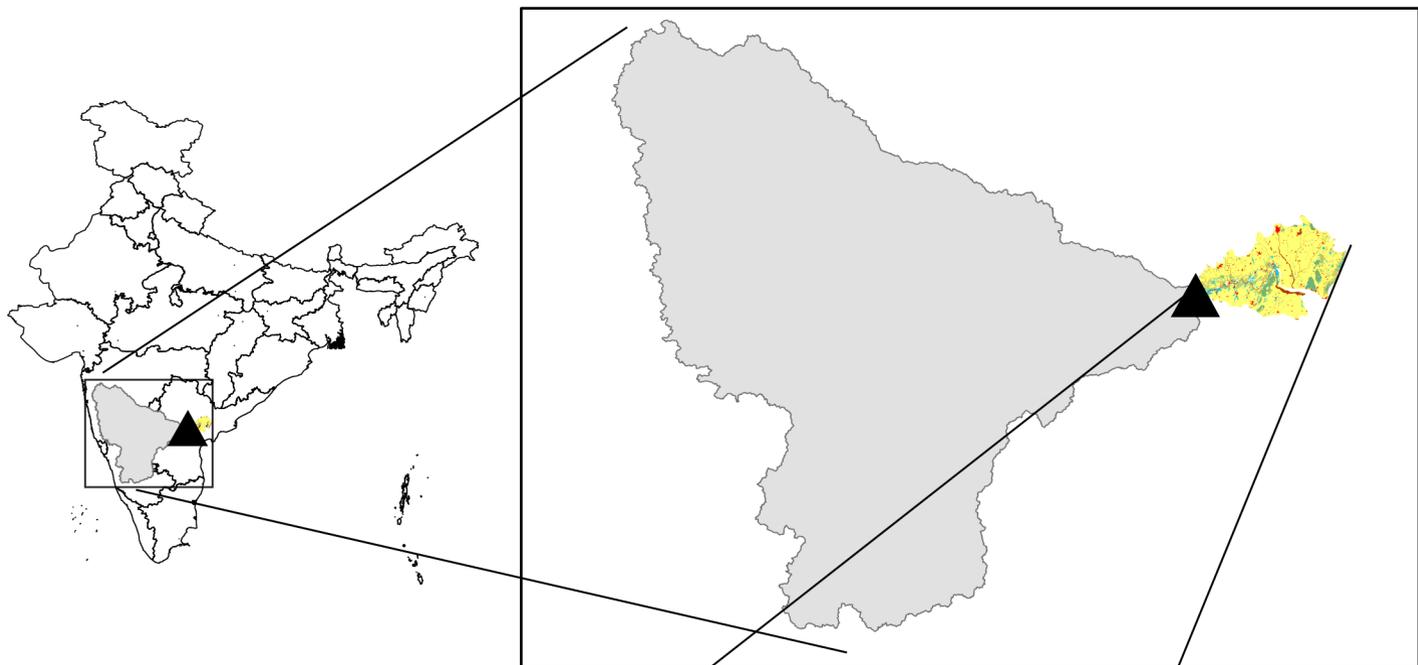
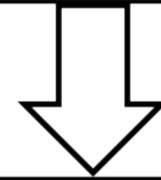
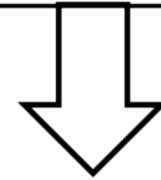


Figure 2.

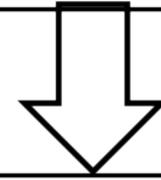
1. Preliminary conceptualization from natural processes and assuming rationale decision maker (CLD1 and SHM1)



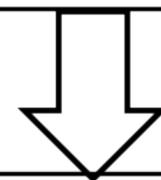
2. Identify stakeholders and conduct semi-structured interviews



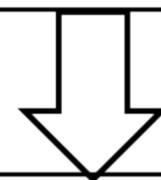
3. Develop alternative CLDs from stakeholder elicitation



4. Develop SHMs using the information in CLDs



5. Validate using historical data



6. Assess water and food security during historical period

Figure 3.

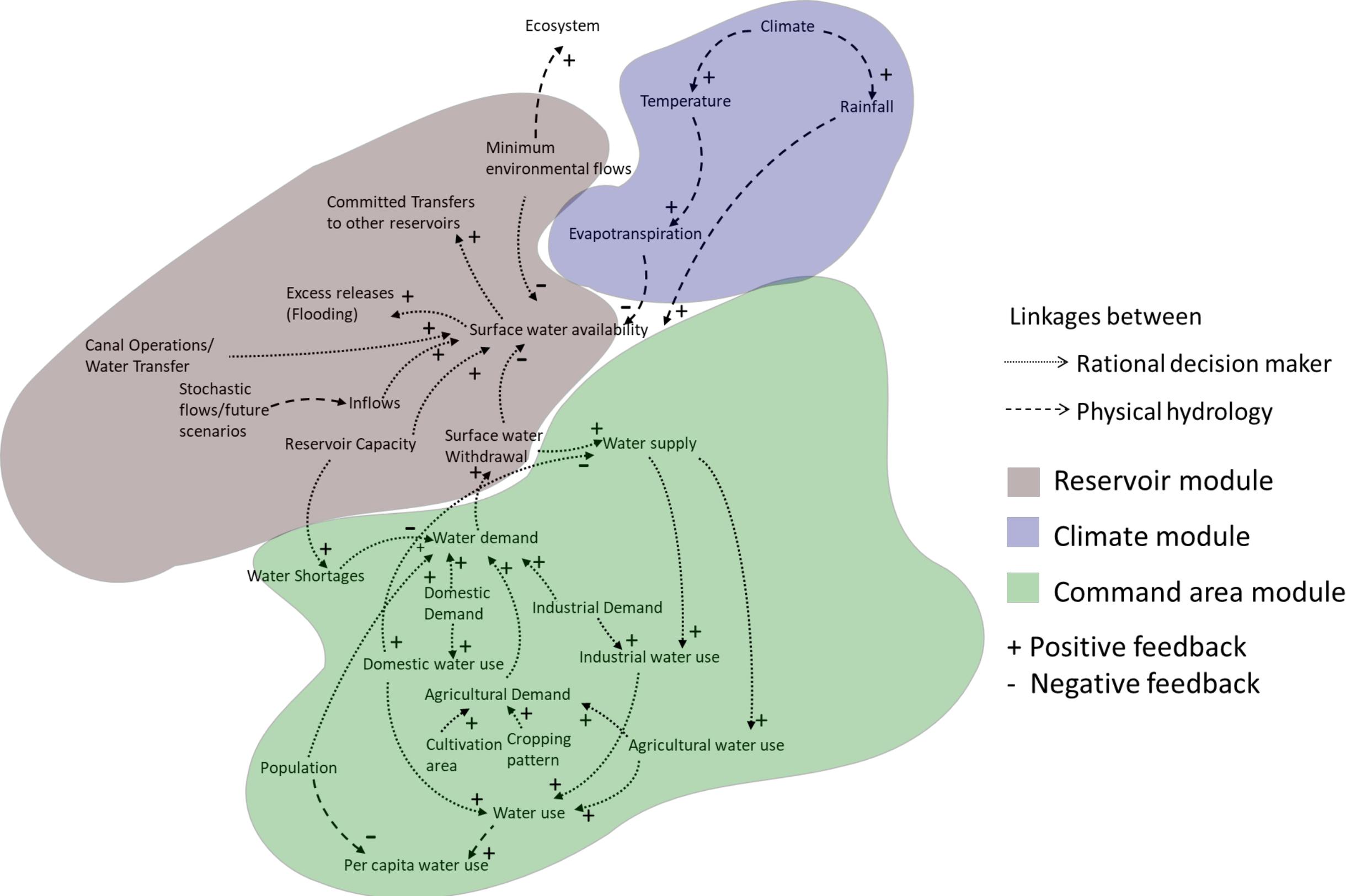
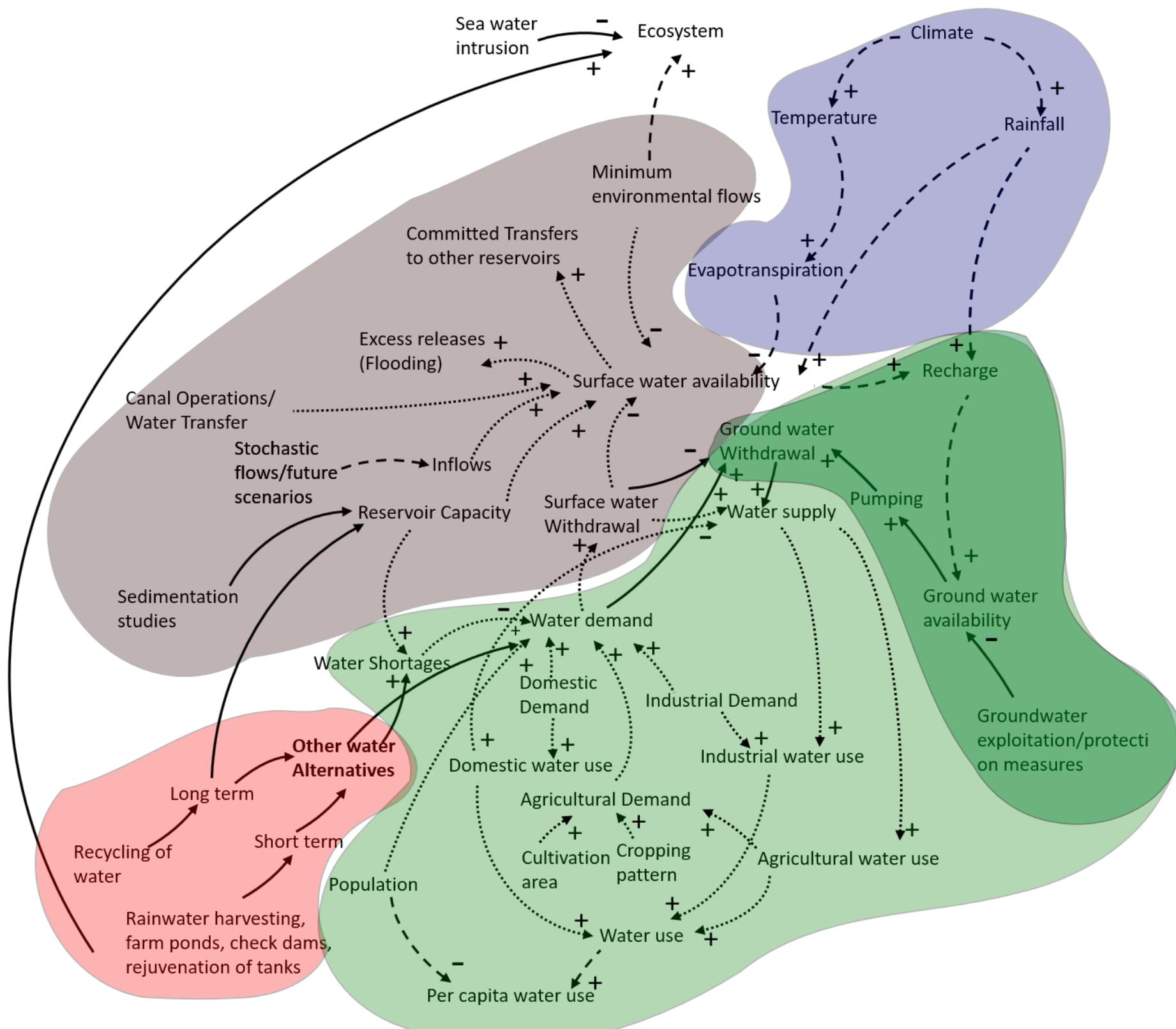


Figure 4.

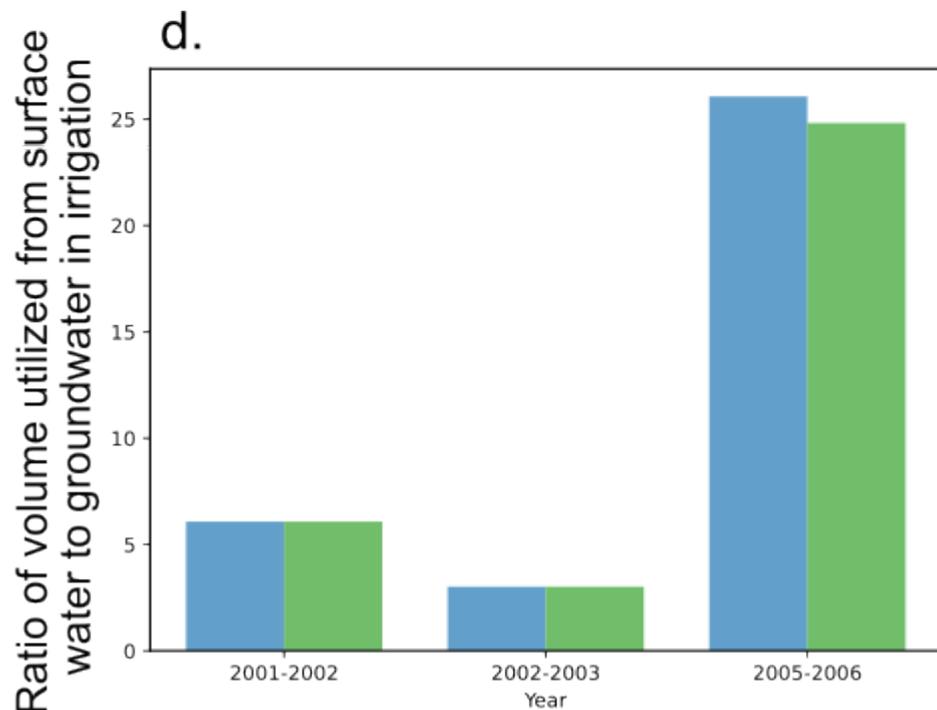
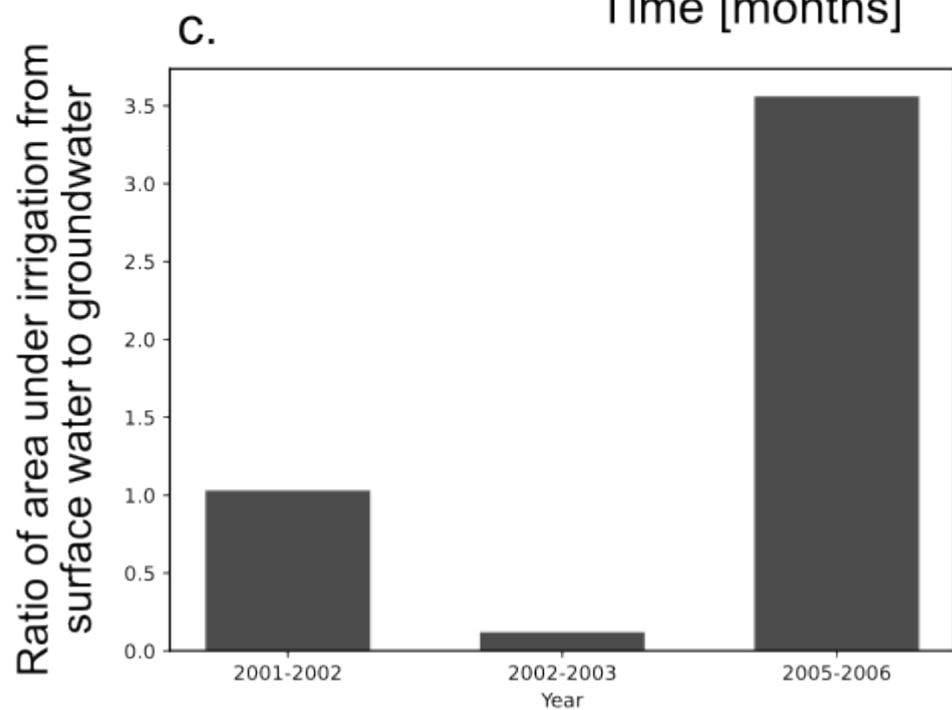
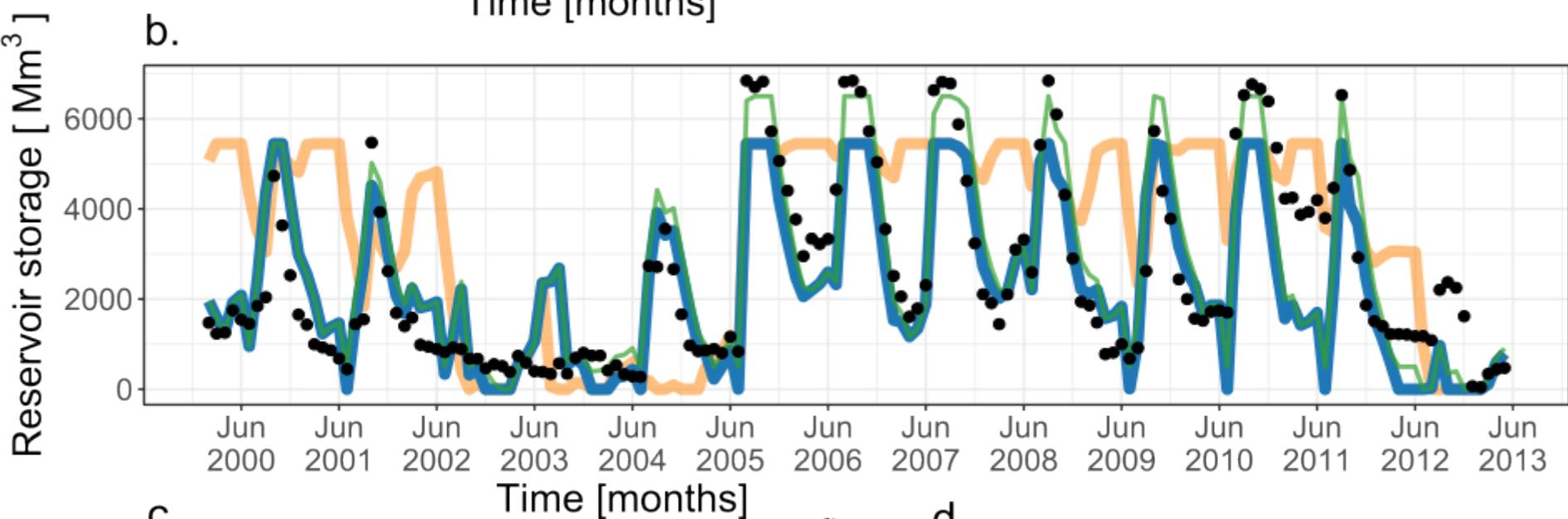
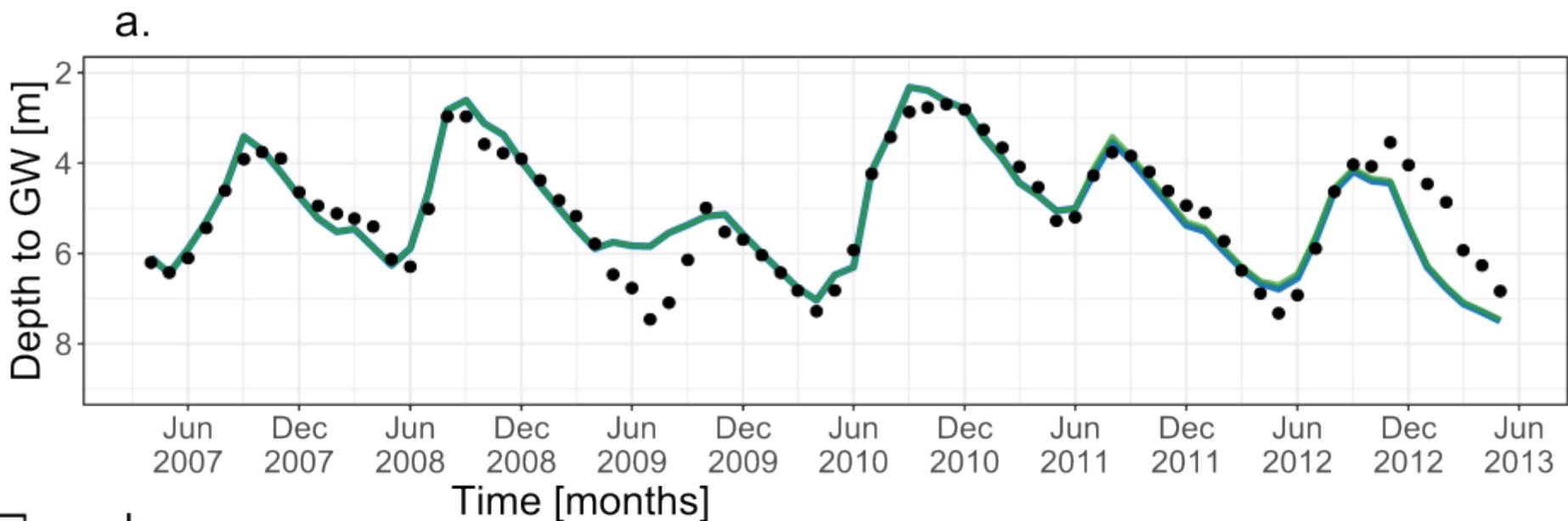


Linkages between

- > Stakeholder interviews
-> Rational decision maker
- - - -> Physical hydrology
- Reservoir module
- Climate module
- Groundwater module
- Command area module
- Consumer model

+ Positive feedback
 - Negative feedback

Figure 5.



SHM1 SHM2 SHM3 Observed

Figure 6.

