CHAPTER FOUR

Framing, analysis, and modeling

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4.1 Introduction: Studying human-water relations

Consider you were approached by the local water agency with the following request: "Help us! The farmers are telling us that they don't have enough water for their crops. We are really concerned that groundwater tables are dropping rapidly, even though we have done our best to encourage more efficient irrigation systems. Why are they dropping? We expected them to increase!" Now, how would you go about explaining the reasons for the declining water tables? Which methods would you use, which research design, in order to give the best possible advice to the water agency? These questions are the topic of this chapter.

In fact, the aim of *Panta Rhei* is to more generally understand changes in hydrology and society, to explore their interlinkages and future evolution, and to provide information that can support more effective policy design and decision-making. Understanding how coupled human-water systems have changed in the past, how they are changing at present, and how they may change in the future is critical for addressing current and future water challenges. From sustainable development and human and ecosystem health to risk management, evaluating the feedback loops inherent in coupled human-water systems while assessing their evolving trajectories under a changing climate is key to achieving long-term sustainability.

Chapter 3 outlined a number of feedback phenomena of coupled human-water systems, arising from archetypes. For example, the "fixes that backfire" archetype may lead to a phenomenon known as Jevons' paradox (or rebound effect) in the context of human-agricultural systems. The paradox is that the availability of water-saving irrigation technology tends to lead to agricultural intensification, soil degradation, and water overuse, instead of reducing water consumption. From reading Chapter 3, we may suspect that the problem the local water agency reported at the beginning of this chapter may be a consequence of this phenomenon. Jevons' paradox is widespread around the world, but it is in stark contrast with the dominant paradigm among many researchers and practitioners that advancing modern irrigation technologies will directly lead to water savings (see Pérez-Blanco et al., 2021). Understanding the root mechanism of this paradox, and identifying more suitable and robust policies that can achieve sustainable water consumption with or without more efficient technologies, requires a well-founded interpretation of the phenomenon across all its facets.

In this chapter, we review a variety of methods and modeling approaches employed in *Panta Rhei*-related studies and detail how each approach highlights different aspects, and how they can be brought together to advance a more holistic understanding of the coupled human-water systems. The purpose of all of these methods is to arrive at an understanding of how the coupled system functions including its interactions and feedback. Suitable policies are those that are able to change these interactions and feedback (which will modify some of the arrows of the associated feedback loops, see Chapter 3) in order to obtain a more desired system behavior, such as sustainable water use in our irrigation example. We refer to methods that have been developed by the Panta Rhei community over recent years while placing them in the wider context of existing research approaches for exploring change in human-water systems and settings used by other social and natural science fields.

Using the image of a prism, we imagine splitting a phenomenon into its constituent aspects (Fig. 4.1). The phenomenon under study here emerges as a result of the interactions between humans and water. For example, farmers' risk perceptions may drive their water use behavior. A lack of disincentives to pump groundwater may result in dry wells before the end of the growing season in areas with shallow aquifers. In reality, our methods make only some aspects visible when there are many. Qualitative methods, such as group discussions, may shed some light on the risk perception of farmers, and quantitative methods, such as groundwater modeling, may provide insights into aquifer depletion. Individually, the methods unravel a part of the phenomenon; together they begin to explain the interactions and the emergence of the phenomena as a whole.

Qualitative data-collection methods, such as focus group discussions and interviews, could be used to interrogate and describe how humans interact with the environment to build a narrative—a chain of causalities. A human-agricultural system serves as one example where focus groups and interviews may unravel how farmers perceive scarcity and abundance created by water-saving technologies. Quantitative data, such as water level recordings in wells, can be used to observe how groundwater levels have evolved over time and to identify the causal relationship between the variables involved. These

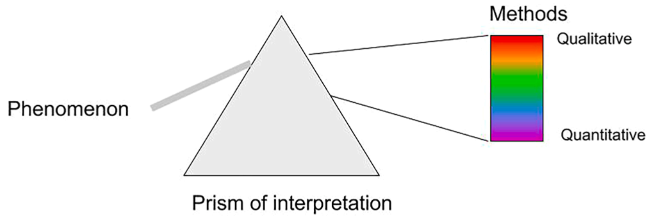


Figure 4.1 The image of a prism of interpretation that could split a phenomenon into its constituent aspects, where each method makes visible only parts of these aspects.

may describe the human-agricultural system with or without invoking mathematical equations to predict future trajectories. Inspired by such descriptions of human-water relations, models may be developed as tools to predict future trajectories of agricultural development, water use, and groundwater sustainability. There is significant value in using quantitative and qualitative methods in tandem in order to explain phenomena arising from coupled human-water systems.

Apart from the research methodology, one also has to choose a study scale. Usually, this will depend on the research question of interest, and scales range from the individual to communities, river basins, regions, or the entire globe. At some scales, certain methodologies are more common because data are easier to collect or analytical methods are more consistent with theory at that scale. For example, participant observation and interviews lend themselves easily to the study of individuals and small groups of people, while at the river basin scale, surveys are usually preferred. At the global scale, statistical and econometric models are sometimes the method of choice. Human-water interactions are often across scales. For example, cultural values drive the drafting of constitutions, which drive water laws, which drive water policies and contracts of the water industry at small scales, and so on (Fig. 4.2b). Conversely, reflecting on the growth and organization of human societies, one can say that the larger entities in Fig. 4.2b are themselves the result of long-term processes interacting at progressively smaller scales. Note the similarities with how energy cascades down through the Earth System, and how water aggregates upward in scale when flow accumulates downstream in a river system (Fig. 4.2a). There are similar timescale interactions in hydrology, e.g., fast water flow and erosion processes interacting with the much slower bed formation processes,

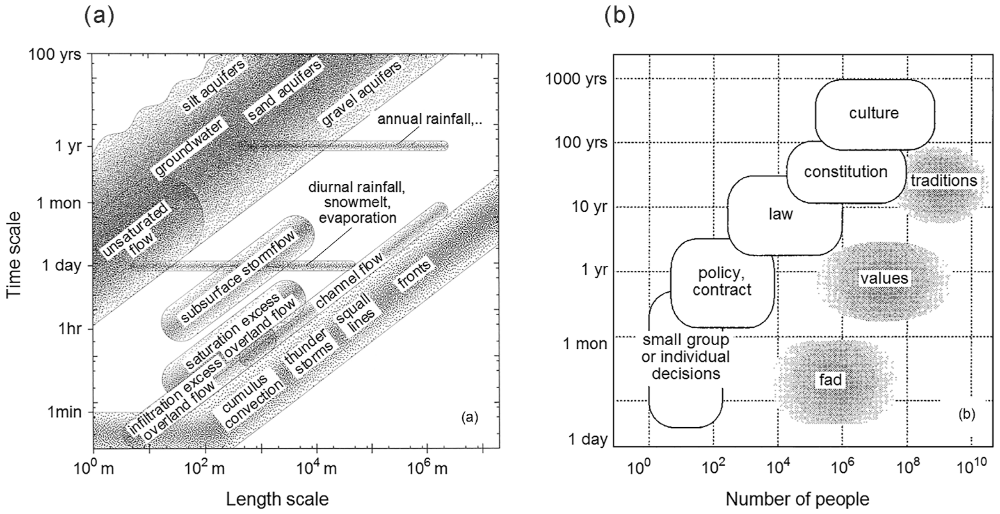


Figure 4.2 (a) Characteristic scales of hydrological processes (Blöschl & Sivapalan, 1995). (b) Characteristic scales of institutional processes (Gunderson et al., 1995).

leading to meander formation (i.e., the phenomenon). In a similar way, fast hydrologic processes (e.g., floods) can lead to much longer-term dynamics of the social system, e.g., changes in policies and laws and construction of infrastructure. These interactions across scales result in coevolutionary processes in human-water systems giving rise to the phenomena studied in this book.

4.2 The scientific method for studying phenomena

4.2.1 Possible steps for framing and modeling human-water interactions

How do scholars explain observed phenomena, how do they bring order to the apparent disorder, how do they assign causalities within the system? Over the past three centuries or more, scholars have developed the "scientific method", the process by which science is carried out. It is a cyclical process that involves making hypotheses about how nature works, deriving predictions from them as logical consequences, and then carrying out experiments based on those predictions to determine whether the original hypothesis was correct and, if not, proposing alternative hypotheses. This methodological setup tends to be more easily applicable to the physical than the social sciences. One of the most famous experiments in scientific history was the Michelson–Morley experiment on the speed of light which eventually led to special relativity. For coupled human-water systems, where the social science aspect is very relevant, this kind of experimentation is rarely feasible. Formal hypothesis testing may be possible in some instances where clear hypotheses exist. In other instances, a creative reasoning process based on clues and explorative analyses may have better chances of unraveling the functioning of the examined system (Blöschl, 2017). On the other hand, observations will always be relevant, and they may be quantitative or qualitative (as alluded to in Fig. 4.1). They are covered in more detail later in this chapter.

Following the scientific method, seven steps have been proposed for framing and modeling human-water interactions (Sivapalan & Blöschl, 2015). The steps are in the spirit of the systems approach (Chapter 3) and account for the particularities of studying human-water systems. The seven steps are as follows:

Step 1: Phenomenon, domain, scale: This step involves developing a general statement of the phenomenon, variables, and setting boundaries for the problem in space and time. The phenomena may include tipping points, regime shifts, and system lock-ins. The phenomena are often obtained from narratives presented by stakeholders and experts from different disciplines. In this step, boundaries need to be set, and a decision needs to be made about which aspects to internalize (i.e., processes that will be represented within the system considered) and which to externalize (i.e., boundary conditions, not influenced by the system behavior).

Step 2: The conceptual model: A conceptual model is developed that describes the system, i.e., (one or more) working hypotheses about the underlying causes of the phenomenon. Since feedback between processes and scales are particularly important, it is often useful to start the conceptual model by drawing causal loops that represent the feedback of the system, as explained in Chapter 3. The drawing of the causal loops may be based on a narrative of the problem or it could be based on preliminary data analyses. Integrating different disciplines and different stakeholders in a research team will likely capture a more realistic conceptualization of the system interactions taking place (Carr et al., 2020).

Step 3: Choice of state variables: If the study involves a quantitative model, the choice of state variables is an extremely important framing step. What is considered a changing variable or a constant parameter depends on the nature of the model and the phenomenon. To be useful, all the variables included in the model should be measurable, either directly or through the use of appropriate surrogate or proxy information. If the purpose of the study is normative (i.e., decision support, see Chapter 2), decision variables that represent possible decisions need to be represented, such as the discharge of water abstractions (Lempert, 2003).

Step 4: Causal factors that affect state variables: Causal factors can be external (prescribed) factors (e.g., precipitation, GDP, legal conditions) or other internal state variables. The causal loop diagrams (Step 2) provide guidance on the choice of causal factors. For example, factors that affect flood risk awareness may include previous experience with damaging floods, economic wellbeing, and cultural factors (such as the value attached to living in a home with a view).

Step 5: Functional relationships by which causal factors affect state variables: The next step is the specification of functional relationships that describe each of the feedback between the state variables as well as the effects of the external forcings. They can be conceptualized using intuition, through recourse to data analysis, taken from literature on related studies, or can be based on consensus principles (e.g., logistic growth). The functional relationship between values and human behavioral response, for example, can be obtained through choice experiments (e.g., Morrison et al., 1999) that explore the judgment of a set of experts or stakeholders through questionnaires.

Step 6: Parameter estimation: In the case of quantitative models, parameters of the functional relationships should, ideally, be inferred from observations of the case studies, although this may be even more challenging than for hydrological models, because of the many coupled processes involved (Brun et al., 2001). Estimating the parameters separately for the individual component models or different timescales may help in the process (Beck, 1999).

Step 7: Model validation and uncertainty: For quantitative models, accuracy, consistency, and generalizability are usually the main criteria for building confidence in

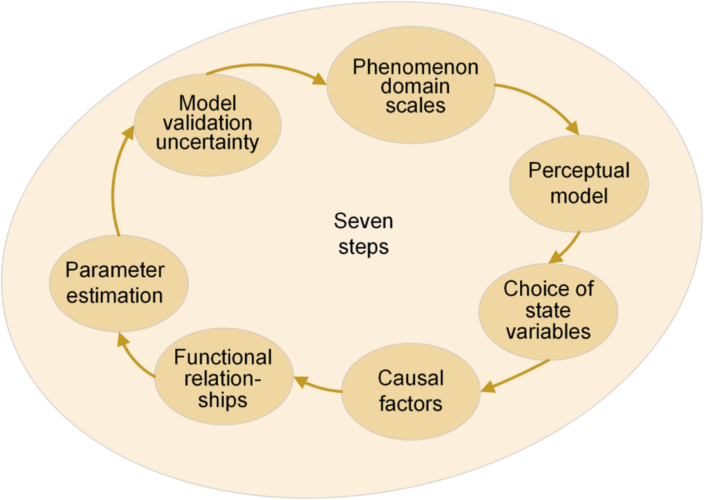


Figure 4.3 Seven methodological steps of framing and modeling human-water interactions (Sivapalan & Blöschl, 2015).

> the findings. If possible, a split-sample method can be used where part of the dataset is used for parameter estimation, and the remainder of the data is used for validation. For more qualitative approaches, other criteria, such as authenticity and trustworthiness, may be more relevant (see Section 4.6 of this chapter).

As illustrated in Fig. 4.3, the framing and modeling is an iterative process (in line with the scientific method) that may involve a loop from Step 7 back to Step 1 (in case the validation is not satisfactory) as well as subloops between individual steps as required.

4.2.2 Framing and modeling on the qualitative-quantitative spectrum

The systems approach is not the only way of studying human-water phenomena (Chapter 2). Often the study is more on the qualitative side of the qualitative-quantitative spectrum. In this case, Steps 3–6 of the above list may be less relevant or skipped, and the remaining steps take on a key role. In other cases, qualitative methods, such as participatory modeling, can add realism to the steps, e.g., by identifying relevant causal factors and functional relationship between variables based on past experience.

In Step 1, problem framing often involves situating a study and system within a historical context. Qualitative data, such as those from interviews, archives, and participant observations, are uniquely situated to provide rich temporal and spatial analysis. Common to more hydrosocial, political ecology, and critical studies, understanding change over time can explain variance in uncertainty, unintended consequences, nonstationarity, and power dynamics (also see Chapters 2 and 6 for similar discussions) that cannot be captured in statistical models (Haeffner et al., 2017, Mukherjee, 2020; Kallis, 2010). Komakech et al. (2012), for example, analyzed how water transfers impacted smallholder farmers and created conflict situations in Tanzania and demonstrated that infrastructures are maintained when power is in the hands of the few. Complementing the historical perspective, problems can also be situated within visions of the future in terms of storylines or shared narratives. Bou Nassar et al. (2021) used focus group data to develop shared narratives, or storylines, across multilingual participants involved in lake management in Guatemala. They combined these with individual semistructured interview data using the process described by Inam et al. (2015), then brought the merged diagrams back to a focus group workshop to reexamine perceived drivers. This process allowed them to center Indigenous Mayan communities, connect perspectives across political cultures, and elaborate hypothesized drivers of eutrophication across macro-, meso-, and microscales.

Shepherd et al. (2018) reflect on the differences between storylines, narratives, and qualitative scenarios as support for decision-making processes in climate and water sectors. They maintain that narratives characterize stakeholder's views, understanding, or perspectives, and their analysis is used to investigate water discourses and/or the framing of issues by the media or policy-makers. Storylines are defined as a series of past events, or as plausible future events or pathways. Thus, emphasis is placed on understanding the driving factors involved and the plausibility of those factors.

Regarding Step 2, focus group data lends itself well to qualitative analysis techniques to understand how and under which conditions social groups come to a consensus, compromise, or create solutions for future problems. For example, multi-criteria analysis can be used to identify attractive solutions across disparate groups, while plural rationality approaches can be used to find solutions acceptable to all, and scenario-based approaches can be used to weigh costs and benefits for different environmental decisions (Scolobig & Lilliestam, 2016). Simulations using qualitative and/or quantitative data can be used in focus groups to qualitatively analyze responses to alternative futures and processes of social learning (Hatzilacou et al., 2007; Warwick et al., 2003; Wheater & Gober, 2013).

Following the image of the prism (Fig. 4.1), much can be gained from exploiting the complementary nature of qualitative and quantitative methods in an interdisciplinary research setting. Quantitative data, such as climate data, have been used in qualitative studies for a long time (Mostert, 2018). The systematic collection of primary qualitative and quantitative data, however, by the same individual or by a research team with a specific view toward integration is a relatively recent endeavor. Insights generated through integrating qualitative and quantitative data are critical for developing a more complete understanding of the multifaceted aspects of human-water relationships and process interactions. Additionally, qualitative research is critical to precede or support quantitative modeling that may aim at exploring uncertainty and identifying the future (unintended) consequences of past and present actions (Ceola et al., 2016). In this section, we outline such an approach where quantitative analysis takes center stage and qualitative analysis has a supporting function in the conceptualization and validation stages. This framing has been prevalent in the Panta Rhei decade. We note, however, that an alternative framing where qualitative analysis is central, supported by quantitative analysis, is also possible (e.g., Lebek & Krueger, 2023; Massuel et al., 2018; Mostert, 2018).

A variety of qualitative analysis methods are available to conceptualize relationships and develop novel human-water concepts. Social science methods have often provided the means to conceptualize human-water relations that underpinned quantitative modeling (Carr et al., 2020). Participatory methods that engage stakeholders in discussing model results, simulations, and the realism of scenarios are equally valuable in validating the quantitative relationships that build upon concepts inspired by qualitative methods. Fig. 4.4 shows a possible pattern of how various methods work together, emphasizing that any interpretation of a phenomenon has elements of both qualitative and quantitative methods.

Consider the example of Jevons' paradox of interpreting irrigation efficiency in Fig. 4.5. The intended water savings often do not materialize with the introduction of irrigation-efficient technologies such as drip irrigation. Qualitative methods, such as farmer group discussions, have pointed to perceived abundance due to water savings that led to the use of saved water by crop intensification (see, e.g., Birkenholtz, 2017). This concept of a farmer's relationship with saved water has inspired quantitative modeling methods that incorporate the perception of water availability in decision-making (Hatch et al., 2022). When cocreated with farmers and calibrated and validated with a diverse evidence base such as local stakeholders, household surveys, and hydro-meteorological data (e.g., vegetation greenness index and groundwater level measurements), it can highlight the need for incentives or disincentives to avoid agricultural intensification (Birkenholtz, 2017). Each method on its own unravels different aspects of the phenomenon but remains incomplete in its interpretation. Only when the right mix of

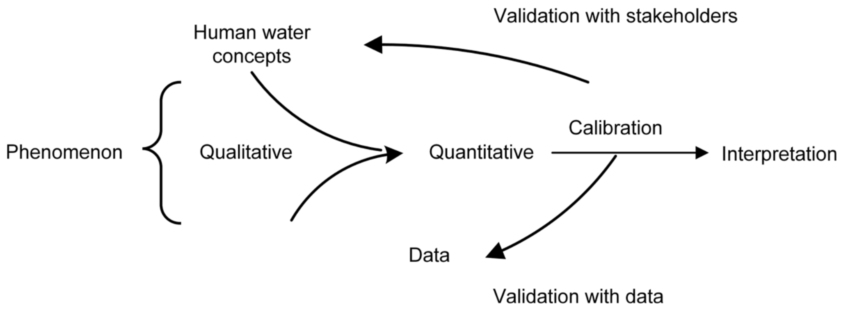


Figure 4.4 Schematic of how quantitative methods can be supported by qualitative methods in order to provide an interpretation of a phenomenon.

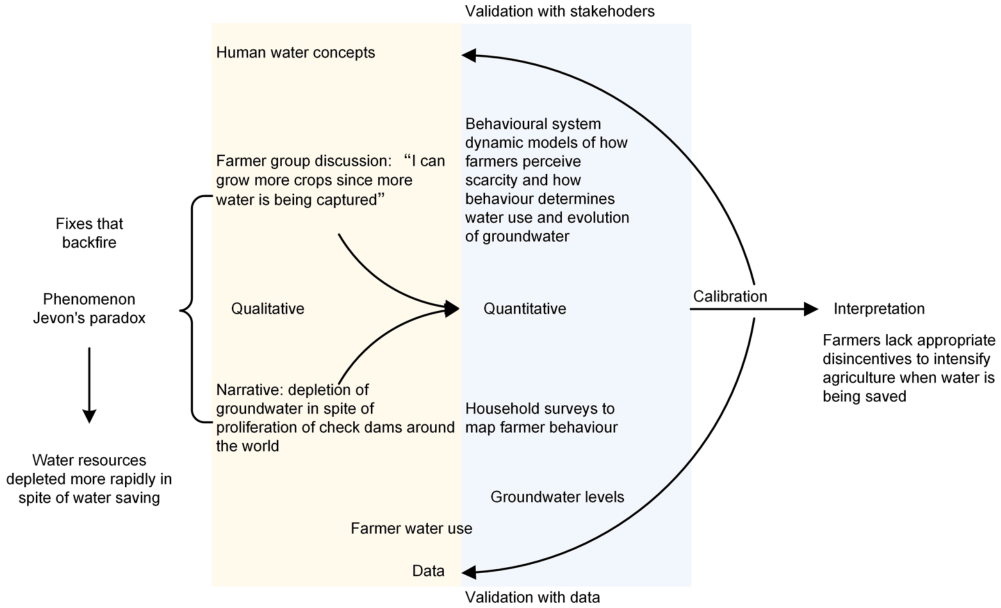


Figure 4.5 Example of using the schematic of Fig. 4.4 to interpret the irrigation efficiency paradox.

methods (colors in the spectrum) is used can the paradox be unraveled and appropriate incentives be designed to avoid the unintended consequences of agricultural intensification on water resources. In this context, we distinguish between three phases of how mixed methods can be used to interpret a phenomenon (see Figs. 4 and 5): problem formulation, analytical method selection, and evaluation.

4.3 Participatory research design

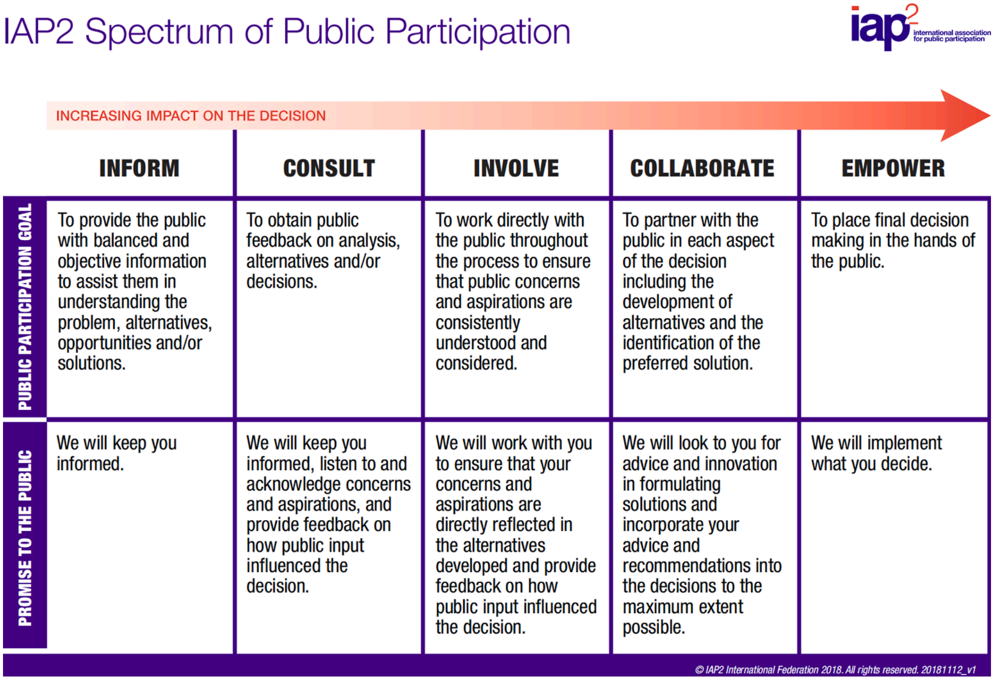
4.3.1 Qualitative participatory research

The emphasis on the role of stakeholders in Figs. 4.4 and 4.5 is motivated by the recognition that the analysis of human-water relations needs to be a multi-stage process. One single analysis, or one single research group, is not expected to provide all the answers. As recently noted by Melsen (2022), it is common in hydrology for research groups to select methods and problems to address based on their expertise and experience rather than based on problem characteristics alone.

The study of human-water relations is very broad, so adopting a wide perspective becomes even more important. To this end, quantitative and qualitative methods can be combined with a participatory angle, where people who are not academics engage in scientific research to interpret a phenomenon of interest. We can broadly distinguish research engaging with participatory or coproductive decision-making (Carr, 2015) from research itself turning participatory or coproductive (Krueger et al., 2016). The use of participation in research methods influences both the validity and impact of the research. Fig. 4.6 shows how different levels of public participation impact the decisions. While some projects seek to collaborate with or empower stakeholders, others are restricted to consulting with or informing stakeholders or perhaps involving stakeholders in developing and validating concepts and models of human–water systems and collecting data.

4.3.2 Modeling with stakeholders

Stakeholders can be involved in quantitative modeling (Walker et al., 2015). Such collaborative has the capacity to make explicit unknown or hidden relationships, identify and make accessible existing datasets, ensure continuous evaluation and validation (see Section 4.6), as well as make the modeled outcomes more relevant and acceptable to research users. Modeling procedures present opportunities for structured engagement with stakeholders. In Sivapalan and Blöschl's (2015) stepwise approach to human–water modeling, the third step of defining the model variables, the fourth step of identifying the causal factors driving changes in the variables, and the fifth step of determining the speed and magnitude of these relationships can all benefit from engagement with people



IAP2 Spectrum of Public Participation

	INFORM	CONSULT	INVOLVE	COLLABORATE	EMPOWER
PUBLIC PARTICIPATION GOAL	To provide the public with balanced and objective information to assist them in understanding the problem, alternatives, opportunities and/or solutions.	To obtain public feedback on analysis, alternatives and/or decisions.	To work directly with the public throughout the process to ensure that public concerns and aspirations are consistently understood and considered.	To partner with the public in each aspect of the decision including the development of alternatives and the identification of the preferred solution.	To place final decision making in the hands of the public.
PROMISE TO THE PUBLIC	We will keep you informed.	We will keep you informed, listen to and acknowledge concerns and aspirations, and provide feedback on how public input influenced the decision.	We will work with you to ensure that your concerns and aspirations are directly reflected in the alternatives developed and provide feedback on how public input influenced the decision.	We will look to you for advice and innovation in formulating solutions and incorporate your advice and recommendations into the decisions to the maximum extent possible.	We will implement what you decide.

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Figure 4.6 Approaches in scientific research design with the public. *Adapted from the IAP2 Spectrum of Public Participation (Nabatchi, 2012).*

embedded in the system that will enhance the realism of the model. In determining variables, a combination of expert opinion and real-world experience can identify measurable variables (either directly measurable or through the use of appropriate proxy information) with suitable data availability (e.g., groundwater level, river height, precipitation rate, income/spending, population density, land area, human preferences, human perceptions, and human actions).

Human and water system models also need to pay careful attention to the process interactions taking place at different temporal and spatial scales (Sivapalan & Blöschl, 2015). For example, rainfall may cause a river to flood in a timescale of days, while implementing flood management approaches may take a timescale of years. Groundwater depletion takes place over years, while policy changes may enable recharge that takes place over decades. Spatially, processes taking place at the farm level will have an impact on the entire catchment, and the actions of a few powerful people can have more impact than the actions of many powerless people. Method selection and research design need to consider the scale of the study being conducted, as well as the temporal and spatial scale interactions. Different models and different model structures have the capacity to address different scales (Kelly et al., 2013, also see Chapter 2). Modelers also need to consider the degree of comprehensiveness they aim to achieve. More comprehensive models that include multiple, detailed, components that nest together may be appropriate for addressing specific management questions in specific places. However, they are effort-intensive. Stylized, less comprehensive models may be computationally simpler and able to provide information on process interactions and long-term feedback, but they may not be able to capture spatial diversity and their application in local decision-making settings may be more limited.

4.4 Collection of qualitative data

Data are, of course, central to explaining human-water phenomena. Chapter 5 will provide a detailed account of quantitative and qualitative data needed for studying human-water systems. Given that the collection of qualitative data closely interacts with the research design, this section will discuss some of the most relevant methods of collecting qualitative data with a view of how they fit into the overall research approach. Participant observations, interviews, focus group discussions, and coded text-based empirical material are often used at relatively small spatial scales (individuals to communities). Surveys, on the other hand, are commonly used at larger scales (individuals to basin scale).

4.4.1 Participant observation

Through participant observation, the researcher observes while simultaneously participating in the situation, e.g., working in the field with farmers, participating in village assemblies, etc. The researcher makes sense of the practices and meanings through what actors actually do, in addition to how they might rationalize their actions when asked (see Section 4.4.2 on interviews and focus group discussions). The observations are captured in field notes, including individual reflections of the researcher and ideally also those of a larger research team (Rangecroft et al., 2020). When the research interest is in social practices or how people give meaning to situations and actions, researchers may benefit from immersing themselves in the situation being researched. As an example of social practices, observations of farmers while at work can reveal how water is used for irrigation purposes, e.g., whether farmers are using flood irrigation or whether groundwater is being pumped. As an example of meanings, in Jambi province (Sumatra, Indonesia), rising water tables were historically considered normal (Merten et al., 2021). Only through agricultural commercialization, land use change, and associated changes in people's livelihoods did rising water tables acquire the more disruptive meaning of flooding, with the associated management responses. To describe this, the researcher lived in Sumatra for 10 months to study six villages along two rivers with different physiographic and socio-cultural characteristics. They qualitatively analyzed their data to identify path dependencies as they emerged, a method that can lend itself well to understanding nonstationary bidirectional feedback loops in human-water systems.

4.4.2 Interviews and focus group discussions

When the research of interest is in people's perspectives or opinions, then interviews are typically conducted. Focus group discussions can be viewed as interviews in group settings, where the exchange of information and opinions between the participants and their group dynamics is as important as the answers to specific questions. Interviews that are one-on-one discussions between the researcher and interviewee have a key benefit over surveys or questionnaires as the interviewer is able to ask further clarifying questions, allowing for greater depth of the empirical material. In some settings, a translator might be involved. The interview may be recorded or notes may be taken.

There are three basic types of interviews as a systematic qualitative data-collection method. In structured interviews, a trained investigator asks predefined and standardized open-ended questions in a specific order to assess all responses based on the same criteria in an effort to reduce interviewer bias. In semistructured interviews, an investigator is trained to ask a set of predetermined questions in order to adapt to the flow of the conversation and to follow up with clarifying questions for deeper probing. In unstructured interviews, a trained investigator uses an open-ended and flexible format that follows the respondent's thoughts in an organic exchange of information.

Interviews can bring to light relationships between aspects that were previously unknown or not explicitly connected. For example, Savelli et al. (2021) interviewed nongovernmental, civil society organizations, and private sector agencies about how their strategy changed during the 2015–17 drought in Cape Town, South Africa. They also interviewed media representatives about whether there was pressure on how reporting was approached during the drought. The information required to answer these questions is not typically available through content analysis of documents and is more detailed than that obtained through surveys. Using these methods, Savelli et al. (2021) found evidence of unevenness of drought experiences and drought resilience trajectories due to race and class.

Focus group discussions, that bring together a group of individuals, might be employed when the interest is in group dynamics or shared sense-making. Hoellermann et al. (2021) convened five focus groups with four to seven participants each in five villages in Tanzania on current and future land-water management. They selected the group format because they wanted to bring out the heterogeneity of farmers within their social and environmental context. The place where interviews or focus groups take place is important (Hoellermann et al., 2021). In group processes, power relations must be managed. Trust and recognition, as well as repeated encounters, are important so that the researcher can get a sense of the authenticity of people's behavior and their answers to questions.

Using more than one data-collection method, theoretical framework, or standpoint is called triangulation. Using triangulation enables unexpected and inconsistent responses to be examined in more detail and forms an element of quality control in qualitative data collection.

Above all, ethical principles need to be adhered to when conducting research with people; see review by Rangecroft et al. (2020). Such ethical considerations are only beginning to attract attention (e.g., Daniel et al., 2019; Klessens et al., 2022) in hydrological, human-water systems, or sociohydrological research. The development and approval of an ethics management plan by an ethics review committee is an essential element prior to any research that engages with humans.

4.4.3 Coding text-based empirical material

Through a process of coding, text-based material is interrogated and annotated with respect to themes that are either preconfigured or emerge from the process of coding itself (see Saldaña, 2013 for 24 different types of coding methods). Coding usually takes several recursions and juxtapositions with theory (Hoellermann et al., 2021). The process of coding can be facilitated by software like MAXQDA, RQDA, Atlas.ti, or NVivo (see, e.g., Mostert, 2015). Such text-based empirical materials are, for example, the transcriptions of interviews and focus group discussions that are recorded with the participants' permission. Transcriptions can be either verbatim or already following a coding scheme.

Coding might also be applied to primary documents, such as historical accounts of land use patterns and the importance of rivers and floods for culture and economy

(Merten et al., 2021), newspaper articles or other contemporary documents, or documents stemming from archival research (Mostert, 2018; Quesnel & Ajami, 2017). For example, Mostert (2015) analyzed children's books with a flooding theme for changing notions of control and care with respect to the water environment over time. Kallis (2010) analyzed archival material, secondary histories, and contemporary publications to narrate the coevolutionary history of water resources development in Athens. Roby et al. (2018) developed a novel search algorithm to scrape media websites in order to extract data, compile, and quantify news coverage on a user-specified topic such as flooding and droughts and ultimately evaluate socio-environmental dynamics.

4.4.4 Surveys

In surveys, a researcher asks structured questions, often with standardized answers. The advantage is time because many respondents can be reached relatively quickly, sometimes even at a large scale through postal or online questionnaires. Due to the standardization, responses can be compared through statistical methods. The disadvantage is that issues cannot be explored in depth. Dissemination via mail or internet holds the risk of excluding certain demographics because they might not be reached as they have no postal address or internet access, or they might lack the language or other skills required to answer the survey. There might also be biases associated with varying response rates across a population.

Surveys are perhaps the most common technique for collecting data on human populations and behavior because they can be analyzed quantitatively using statistical models. Daniel et al. (2020), for example, used precoded, closed-ended questions, such as five-point Likert scales, to collect data from 325 mothers in rural Indonesia to explore household water treatment and use. By analyzing the data through principal component and mediation analyses, they were able to determine a causal pathway showing that the socio-economic characteristics, such as education levels of households, shape their attitudes and perceptions, which in turn influence household water treatment use. Survey sampling methods usually use simple random or stratified random sampling. For example, Scolobig et al. (2012) stratified according to gender, age, and education to attain a representative sample across multiple levels of flood hazard exposure. There are also a number of studies related to collecting psycho-socio-graphic data of urban water users both through surveys and online platforms, e.g., gamification (Cominola et al., 2018, 2021).

Classic survey designs to collect data on water use and perceptions include batteries of questions to operationalize predefined variables (Flint et al., 2016). Q-method is a ranking survey that can be employed in focus group settings. It collects both quantitative and qualitative data, to be analyzed quantitatively and qualitatively, usually to create typologies of stakeholder viewpoints, such as the study by Lynch et al. (2014) of diffusion of water resource policy.

4.5 Models

If the study is more on the quantitative side of the qualitative-quantitative spectrum, models become the main tool for testing the hypothesized functioning of the system against observations. Taking the example of the irrigation paradox again, the description of relationships provided by participant observations and interviews may be formulated mathematically in the language of system dynamics models and agent-based models (ABMs). The behavior toward water use can be modeled as a function of risk perception, water scarcity, and whether or not farmers have adopted the technology. On the other hand, at even larger scales (individuals to global scale), economic and behavioral models, statistical and econometric models, integrated assessment models, and general equilibrium models are common approaches.

4.5.1 System dynamics models and causal loop diagrams

The quantitative system dynamics modeling approach is particularly well suited to the analysis of human-water systems because it breaks complex systems down into their components and makes explicit the relationships and feedback from which hypotheses of system evolution can be developed. The validity of the mechanistic process understanding can be tested against observed or expected system dynamics occurring in reality.

The starting point of the development of system dynamics models is usually causal loop diagrams. A causal loop diagram is a graph of state variables linked by arrows representing causality, often with a sign or strength of the causal relation. Step 2 of the seven-step procedure of Section 4.2.1 and Section 4.2.2 explains how causal loop diagrams can be constructed. Further guidance is given, e.g., by Inam et al. (2015) who qualitatively analyzed semistructured interview data on soil salinity management in Pakistan and developed a technique to guide respondents through the development of mental models (that encompass the problem variable, causes and consequences of the problem, and feedback between the different parts of the system). Olabisi (2010) compared researcher-generated and stakeholder-generated causal loop diagrams and found that the two contained almost entirely different variables and types of positive feedback.

$$\frac{dx(t)}{dt} = a_{11}x(t) + a_{12}y(t)\ldots \text{ how water } (x) \text{ is affected by humans } (y) \tag{4.1a}$$

$$\frac{dy(t)}{dt} = a_{21}x(t) + a_{22}y(t)\ldots \text{ how humans } (y) \text{ are affected by water } (x) \tag{4.1b}$$

Steps 3 and 4 of the seven-step approach build on the causal loop diagram. They can be directly transformed into the equations of a system dynamics model. For illustration, we chose a very simple feedback model represented by the feedback loops of Fig. 4.7a. We have chosen two state variables in Step 3, where x represents water availability and y represents human water consumption. The left arrow in Fig. 4.7a represents the way in which water (x) is affected by humans (y), while the right arrow represents the way in which humans (y) are affected by water (x). One possibility of framing this relationship is a coupled differential equation (Eq. 4.1(a–b)).

Eq. (4.1a) states that the change of water availability with time depends on water availability itself and human water consumption. The second equation states that the change of human water consumption with time depends on the water availability and human water consumption itself, but in a different way than in the first line, as the parameters a_{11}, a_{12} may be different from a_{21}, a_{22}. The two equations are coupled as y appears in the first equation and x in the second. If a_{12} is negative, a large value of y will result in a reduction of x, which can be plotted as a "–" sign in the causal loop diagram. If a_{12} is positive, a large value of y will result in an increase of x, which can be plotted as a "+" sign in the causal loop diagram. If $a_{12}>0$, $a_{21}>0$, both causal connections are "+", and the resulting feedback will be positive (exacerbating feedback or self-reinforcing feedback). Large human water consumption will cause more water to be available (e.g., by constructing water infrastructure), which will increase water consumption even more. This will result in exponential growth and (in reality) an eventual crash. If $a_{12}<0$, $a_{21}>0$, the left causal connection is "–", while the right is "+", and the resulting feedback will be negative (or balancing feedback). A large human water consumption will cause less water to be available (e.g., because of higher prices due to water scarcity), which will decrease the water consumption. This will tend to stabilize to an equilibrium. If $a_{11}\neq 0$, $a_{22}\neq 0$, x and y will also depend on themselves and the system acquires memory. Depending on the parameters a_{11}, a_{12}, a_{21}, a_{22}, the solutions to Eq. (4.1)(a–b) can take

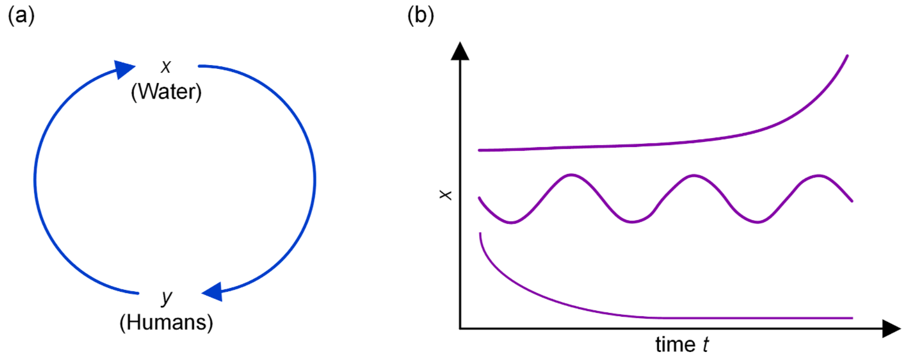

Figure 4.7 (a) Very simple feedback loop between two variables, where x represents, e.g., water availability, and y represents human water consumption. (b) Some of the solutions to Eq. (4.1) representing the feedback loop in (a). The type of solution depends on the parameters a_{11}, a_{12}, a_{21}, a_{22}.

different forms (instability, i.e.,., exponential growth, stable periodic behavior, stability around an equilibrium point) as illustrated in Fig. 4.7b, and thus represent different phenomena of human-water systems. See, for example Pande et al. (2014), who constructed a similar nonlinear dynamical system. They determined the parameters based on endogenous growth theory to explore the rise and dispersal of water limited societies. Real world human-water systems are, of course, more complex, as presented throughout this book. The ensuing dynamics also becomes more complex because the loops are interconnected, either in parallel or in line (Chapter 3). Additionally, the variables x and y can operate on fast and slow timescales, respectively, as is often the case in human-water systems (Sivapalan & Blöschl, 2015). One example is Jevons' paradox of human-agricultural systems, where water extraction is a fast process, and recognition of water overuse by society is usually a slow process. Such fast-slow dynamics lead to coevolutionary processes.

Causal loop diagrams are also very useful in their own right even without developing equations from them for better understanding and communicating coupled systems. They can be a bridge connecting the quantitative and the more qualitative methods (see Section 4.2.2). An example of a causal loop diagram of the Aral Sea in Fig. 4.8 does not necessarily require building a model. The left panel shows the 1960 versus the present shoreline. The right panel shows a general framework coupling various possible elements of the dynamics. Blue arrows indicate positive feedback, red arrows indicate negative

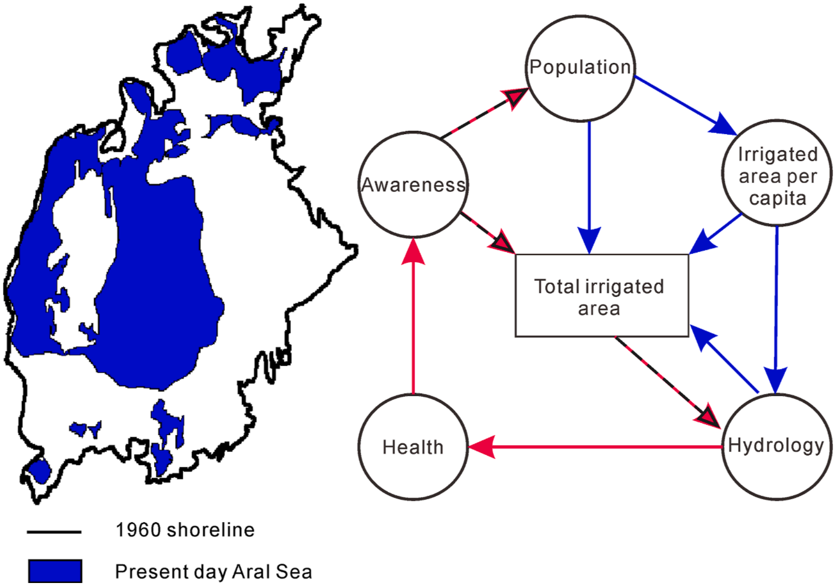

Figure 4.8 Conceptualizing the desiccation of the Aral Sea through the lens of a system dynamics model based on a causal loop diagram. *From* Pande and Sivapalan (2017).

feedback, and dashed red arrows indicate weak negative feedback. The collapse of the Aral Sea may be attributed to weak institutions that could have otherwise inhibited the expansion of total irrigated area. This happened in spite of heightened concerns for environmental hazard.

Given that the system dynamics modeling approach lends itself so well to the analysis of human-water systems, it is not surprising that system dynamics models have rapidly evolved over the last decade, especially in the fields of coupled human-water systems and sociohydrology. Early sociohydrology models focused on human-flood systems (Di Baldassarre et al., 2013), and they are further discussed in Chapter 6. Barendrecht et al. (2019) expanded the model of Viglione et al. (2014) to include the impact of flooding awareness and preparedness on damages experienced during a series of flood events. The work of Barendrecht et al. made advancements in addressing a key challenge for human-water models; that of estimating the values of model parameters using surveys, narratives, land use maps, and literature for the Elbe River in Dresden, Germany. Parameters determine how the variables change. Parameter estimation (Step six of seven in Sivapalan and Blöschl's (2015) human-water modeling) can be difficult in human-water system models due to the complex interactions between the processes and system heterogeneity that may complicate the ability to generalize between different settings. Barendrecht et al. (2018) tackled the challenge of estimating the parameters for preparedness and awareness using a Bayesian inference approach with data uncertainties considered.

Human-water system dynamics models have also emerged in other contexts, interpreting diverse phenomena such as agricultural development, reduced environmental flows, community sensitivity to environmental damage, changes in land management, and agricultural water use (Pande & Savenije, 2016; Liu et al., 2015; Kuil et al., 2016, 2019; Carr et al., 2022). Ilyas et al. (2021) developed a system dynamics model to interpret the rebound effect (irrigation efficiency paradox) as a function of basin characteristics and identified global hotspots that may be vulnerable to the paradox. Such modeling unraveled several "fixes that backfired" (Chapter 2). Using a system dynamics model, Moulds et al. (2021) suggested that urban flood risk management that is rooted in propoor water governance will reduce social inequality and engender sustainable development. Van Emmerik et al. (2014) provided a similar system dynamics representation for basin scale coevolutionary dynamics, using environmental awareness as the key intermediary state variable that counteracts economic growth with improved environmental quality. They calibrated the model on observed flows and validated it in terms of simulated changes in water policy as a response to heightened community sensitivity. This model was further developed by Elshafei et al. (2015) and Roobavannan et al. (2017a) by incorporating the concept of community response based on socio-logical theories to interpret the phenomenon of "successful adaptation," e.g., in the Murrumbidgee River Basin in Australia.

In another example, Kuil et al. (2018) focused on drought management, where the role of farmers' decision-making processes on crop choices as a response to water availability was modeled to show how additional water that was saved through technology improvement was reallocated to farmland instead of flowing downstream (Jevon's paradox). Gonzales and Ajami (2017) assessed human behavior dynamics in response to various drought events in California with different severity and length over the past 4 decades and developed a social memory model for three cities in the San Francisco Bay Area of California. They demonstrated how public awareness due to drought severity can lead to long-lasting social and structural change in water use.

Some human-water system models, such as sociohydrological models, typically endogenize human responses to changes in the water system in order to capture the two-way feedback between water and society (Blair & Buytaert, 2016). As such, they build on the established field of system dynamics (Forrester, 1993), triggered by research into Limits to Growth (Meadows et al., 1972), and can be used to explore the underlying processes driving human-water interactions, model system behavior of the past, present, and future, and explore possible impacts of hydrological or societal changes. System dynamics models, however, tend to represent social processes in a simplified way.

4.5.2 Agent-based models

While system dynamics models often represent processes in a spatially aggregated way, ABMs are more naturally capable of describing spatial relationships between people. In this context, an "agent" is either an individual or a group of people. ABMs can capture the heterogeneity of different agents, as each agent is allocated specific system rules and functional forms. They can also include spatial variability such as flood risk and varying social network structures (Aerts, 2020; Bonabeau, 2002; Du et al., 2017). Based on the rules of how the agents make decisions, the models are advanced in time in a stepwise fashion, and for each time step, the system state is updated based on the outcome of the rules of the previous time step.

Ertsen et al. (2014) argue that water system modeling efforts need to include long, medium, and short-term views that start at a small scale (where the ABM approach is suitable). This argument is based on their analysis of ancient irrigation systems where the formal and informal institutions that maintain system stability and functioning (i.e., water sharing rules) grow out of the interactions that take place at the individual level. Using empirical data, ABMs have also been used to test critical theories about human and natural systems (Janssen & Baggio, 2017). ABMs, like system dynamics models, reduce the representation of social processes to (simplified) quantifiable processes. Instead of aggregate variables (as in system dynamics models), the unit of analysis is the individual agent. This limits the representation to those social theories that are manifested at a level of individuals or groups.

As Fig. 4.9 illustrates, ABMs provide a platform to simulate the behaviors, decisions, and actions of various stakeholders, entities, and institutions (referred to as "agents" in ABMs), regardless of scale. They are well equipped to assess population heterogeneity, interactions (with nature and among humans, including transaction costs), local realities, policy priorities, and inequitable impacts as they explicitly account for the role of individual actors and micro-level constraints (Berger et al., 2006; Berger & Ringler, 2002; Berger and Troost., 2014). For example, ABMs have been applied to agricultural systems to model individual farmers, their spatial interactions with each other and to the natural environment, as well as the consequent biophysical, economic, and social processes at different spatial and temporal scales (Berger et al., 2006; Berger & Troost, 2014; Du et al., 2020; Dziubanski et al., 2020). They do so by integrating and coupling submodels for hydrology, crop growth, economic decisions, social, institutional aspects, and network interaction within an integrated modeling framework (Berger et al., 2006; Berger and Troost., 2014; Dziubanski et al., 2020; Ghoreishi et al., 2021).

In ABMs, the functional relationships or rules can be inferred from a causal loop diagram (if few agents are involved), similar to the equations of system dynamic models (Eq. 4.1a and b). However, the rules usually involve probabilities to account for the incomplete knowledge at the level of individual agents. Fig. 4.10 presents an example of

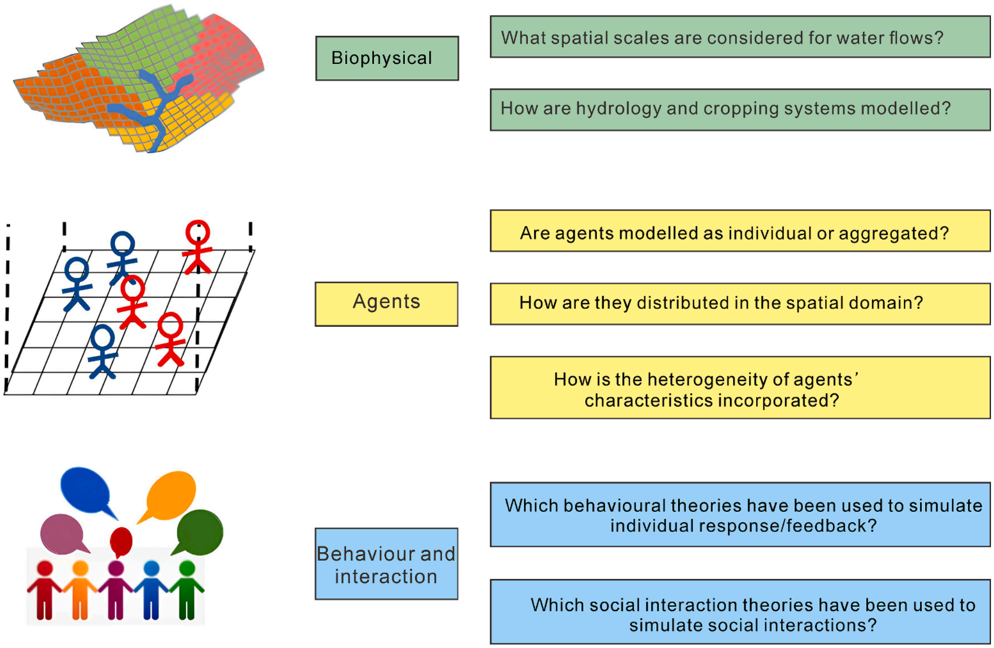

Figure 4.9 Agent-based models describe how agents interact with each other and the biophysical world. *Adapted from Alam et al. (2022).*

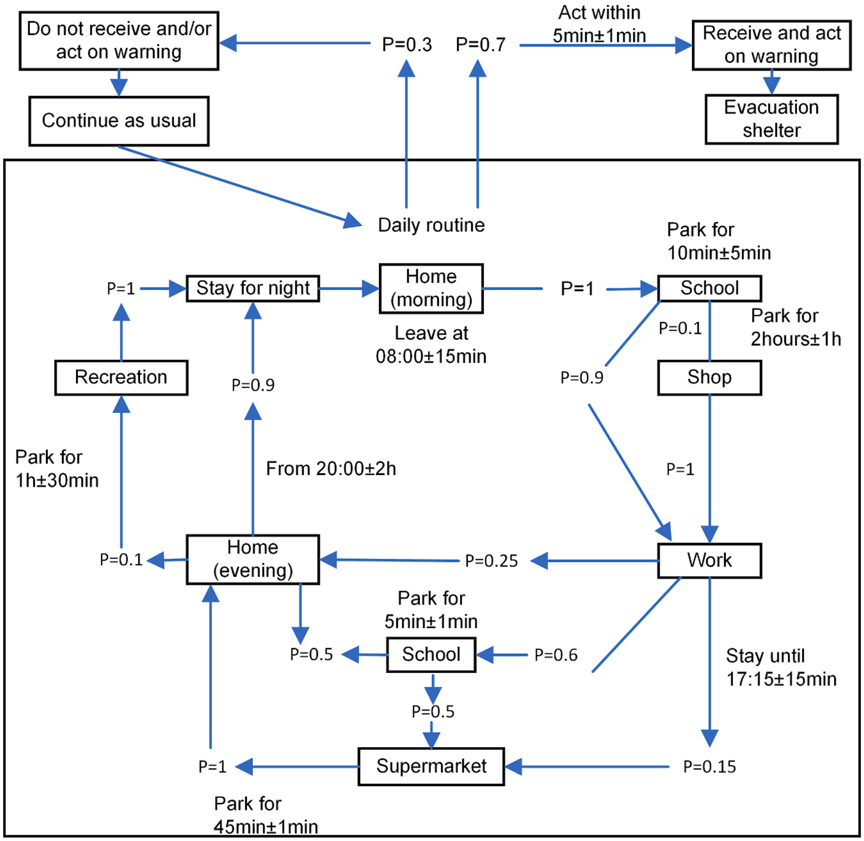

Figure 4.10 An agent-based model of the daily routine generated from travel survey and census data for a female employed agent from a household of four (see Step 5). The agent starts the day at 8:00 a.m., with a standard deviation of 15 min; she travels to work via school to drop children off, with a $P = .1$ probability of visiting the shops en route, etc. This daily routine is interrupted when she becomes aware of a flood incident, e.g., she will choose to evacuate to the nearest shelter with a probability of $P = .7$. *From Dawson et al., 2011*.

an ABM which is based on the results of a survey carried out for flood incident management to assess: (a) how agents behave under normal conditions that determine where they are at the start of a flood event and (b) how they respond to a flood event. Each agent is described in terms of their possible states, the actions they can take, and the transitions between states. To capture the inherent variability and uncertainties in human preferences, the daily routines are described in probabilistic terms. In such an ABM, even if the behavior of individual agents is simple, collectively the model can exhibit complex, emergent patterns because of the interactions between individuals.

Dziubanski et al. (2020) explored the "successful adaptation" phenomenon by linking an ABM with a semidistributed hydrological model to assess how farmers make decisions to allocate land to conservation (to reduce downstream flood risk) rather than cultivation as a response to socio-economic drivers and impacted peak runoff. Crop prices, as opposed to crop yields or conservation subsidies, often drive farmers' conservation practices and hence peak runoff of the basin. Ghoreishi et al. (2021) explored the rebound effect in the Bow River Basin in Canada using an agent-based agricultural water demand model to interpret why agricultural water use has increased in the basin in spite of irrigation system improvements to reduce water losses. This allowed researchers to explore which practices could be adopted to resolve the unintended effect, e.g., by encouraging more community participation and water use restrictions.

Yoon et al. (2021) modeled Jordan's water system as a hierarchy of multiple water agents at various scales. The authors interpreted regional limits to growth and the "success to the successful" phenomenon (Chapter 3). They found that regional water insecurity will make low-income households more vulnerable and highlighted the needs for both the supply and demand sides to alleviate critical water insecurities. Gonzales and Ajami (2019) developed an ABM for the Sonoma County Water Agency in the Bay Area, California, to evaluate and model water diversification strategies through a goal-based trading mechanism. They found that collective action toward infrastructure development can lead to a more cost-effective water resilient outcome. By exploring system behavior from individual interactions, ABMs are particularly well suited to helping understand unintended or unexpected human-water interactions in space and time. Multiagent cellular automata (MACA) are examples of such possibilities that combine ABMs with economic and behavioral models (Kremmydas et al., 2018). Use of such methods enables unpacking unsustainable outcomes. Understanding them can foster more resilient outcomes in the future.

4.5.3 Economic and behavioral models

Economic models of human behavior are often associated with rational decision making, where agents' decisions are assumed to be driven by maximizing their utilities. "Utility" is a concept that represents the worth or value of a good or service or, in other words, a measure of the satisfaction or happiness obtained from each decision. The utility function ranks the preferences of a person or group of persons. Maximum utility would thus imply the "best" choice (in the eyes of the person choosing). It is widely used in neoclassical economics in which the production, consumption, and pricing of goods and services are assumed to be driven by the supply and demand model.

In reality, people do not always decide on the basis of utilities, as discussed by Bertassello et al. (2021). The authors highlight that while beliefs may influence the perceived distribution of events when/if an agent is maximizing her expected utility, often preference structures describing individual utilities are treated as fixed in more traditional economic models. Though utility theory has richer formulations in representing emergent behavior and preference structure (Müller & Levy, 2019), this niche can be filled by behavior models that excel at describing how variation in values influences choices that are made. For example, Li et al. (2017) explored the operational value of weather and climate services for informing agricultural practices by considering heterogenous risk attitudes. They found it is strongly impacted by the behavioral attitudes of farmers with regard to perceptions of risk and uncertainty, underlining the need for models that consider such aspects. Traditional representations of rational decision-making may also be useful to provide benchmarks for comparison, even when it is understood that they do not adequately represent actual human behavior.

One context where choices are made is the human-agricultural system. The literature typically simplifies the complex decision-making process faced by farmers by representing each possible combination of crops, timing, water application, and capital as a representative crop with unique characteristics, where agents have to decide on the crop portfolio that maximizes their sense of satisfaction or utility (Graveline, 2016). Such microeconomic models have been used to interpret irrigation fixes. For example, drip irrigation can backfire when adequate incentives are not in place for farmers to constrain their irrigated areas, change to less water-intensive crops, or decrease total water used. For example, small-scale farmers in Rajasthan, India, increased the total amount of water applied in response to subsidies for drip irrigation. Meanwhile, farmers in the Lower Rio Grande Basin in New Mexico, USA, increased their irrigated areas in response to the same incentive (Grafton et al., 2018). As an example of a coevolutionary model (Giuliani et al., 2016), each farmer agent in the Adda River Basin, Italy, selects their crop on an annual basis and the watering option on a daily basis by optimizing a utility function (their income); their choice is retrofitted to the lake operator upstream who dynamically adapts the lake release to changing water demand.

The form of the utility function in programming models can be "normative," where the researcher proposes an objective or set of objectives that the agents aim for (e.g., profit maximization) (Quiggin & Chambers, 2006). The form of utility function can be "positive," where the researcher leverages a database representing agents' realized decisions under specific technological, environmental, and market information. Certain risk perceptions across agents can also be modeled by formulating different utility functions that variously handle agents' perception of risk (Giuliani & Castelletti, 2016), from risk neutral attitudes to fully risk averse ones. Giuliani and Castelletti (2016) conceptualized a lake operator's preference between balancing flood control and irrigation supply by a multilateral negotiation. Multiple virtual agents independently optimized different value functions of a more or less conservative attitude depending on the recent occurrence of wet or dry extreme events. This model was based on the concept of availability bias (Tversky & Kahneman, 1973).

The emergence of the field of coupled human-water systems has driven the development of models that go beyond piecewise representations of human agents and integrate full-fledged hydrologic and human system models (Essenfelder et al., 2018). Special attention has been given to regional limits to growth, based on endogenous growth theory (Pande & Ertsen, 2014; Pande et al., 2014) as well as intertemporal welfare maximization formulations to interpret the levee effects using hypothetical examples (Grames et al., 2016). Using dynamic welfare optimization of a typical society that is exposed to flood events and corresponding damages, Viglione et al., 2014 identified two societies that survive: rich and poor, akin to Danube (rich) and Mekong (poor) societies.

Novel behavioral theories have more Grames et al. (2016) recently been used in diverse settings and allow for the progressive integration of economic theory and the responses of empirically observed agents. The values-beliefs-norms (VBN) theory (Caldas et al., 2015) has been applied widely, e.g., in the context of interpreting the emergence of better water and land governance in response to severe environmental degradation in Australia (Roobavannan et al., 2017a; Roobavannan et al., 2020; Wei et al., 2017). In representing the role of uncertainty in decision-making, prospect theory has been extensively used to explain asymmetric human response to wet and dry conditions. Tian et al. (2019) applied the theory to explain how individuals assess the likelihood of experiencing an equivalent level of water loss during dry seasons compared to wet seasons in four arid inland basins in Central Asia and China. Similarly, Di Baldassarre et al. (2017), Ghoreishi et al. (2021), and others (e.g., Fischer et al., 2021) have gone beyond system dynamics models and implemented behavioral theories, such as the theory of planned behavior and limited rationality in human decision-making, to explore phenomena such as reservoir and rebound effects.

4.5.4 Statistical and econometric models

Economic and behavior models of human-water relations, such as farmer perception of water abundance, are informed by data-collection methods, such as surveys, through statistical and econometric models. For example, Gonzales et al. (2017) developed a conservation trading mechanism using a cost minimizing decision-making optimization algorithm driven by local and regional priorities and capacities to enable water-saving actions across a number of interconnected utilities to collectively respond to drought and water scarcity. Mondino et al. (2020) evaluated longitudinal surveys, i.e., using two surveys where the same households were surveyed in 2005 and 2018, in two villages in the northeastern Italian Alps that were affected by debris flows in 2000 and 2002. The authors assessed how risk awareness changed over time as a result of the events to show how the population migrated to a levee protected area. Such quantitative analysis, complementing qualitative description, of survey data aims to reduce the information in surveys to estimates of the effects of factors such as socio-economic characteristics on outcome variables of interest such as risk awareness.

Similarly, Sanderson et al. (2017) statistically analyzed cross-sectional survey data to understand the effects of values on beliefs and norms in the behavior of farmers and nonfarmers regarding their willingness to manage the commons in the Central Great Plains of Kansas, USA. Full information maximum likelihood estimated the parameters of a nested set of equations to support the hypothesis that values first influence beliefs and beliefs in turn influence norms (VBN theory of culture) before both influence behavior. Daniel et al. (2020) and Klessens et al. (2022) developed Bayesian belief networks on risk-attitude-norms-ability-self-regulation (RANAS) based on household survey data to understand adoption behavior with respect to water technology and conservation practices in Indonesia and the Lower Mekong in Vietnam. As Fig. 4.11 shows in the context of efficient water use behavior, partly encapsulating VBN theory, RANAS models are statistical models populated by cross-sectional survey data on psycho-social variables such as perception of risk, attitude, and prevalent norms, which in turn are assumed to drive outcome behavior (Moncaleano et al., 2021). Roobavannan et al. (2020) and Lyu et al. (2020) have also used econometric time series analysis to project time series of economic variables, such as basin scale GDP and migration, respectively, into the future in order to assess successful adaptation. For example, Lyu et al. (2019) unraveled rural to urban migration in Jiangsu province of China, using a microeconomic model that maximizes income expected from migration and found that rural unemployment explains the adaptive behavior of farmers to move to urban areas.

4.5.5 Integrated assessment models and general equilibrium models

Most of the models that have been discussed until now are either at the individual scale or at the river basin scale. Yet, as Chapter 10 on global systems highlights, several advances

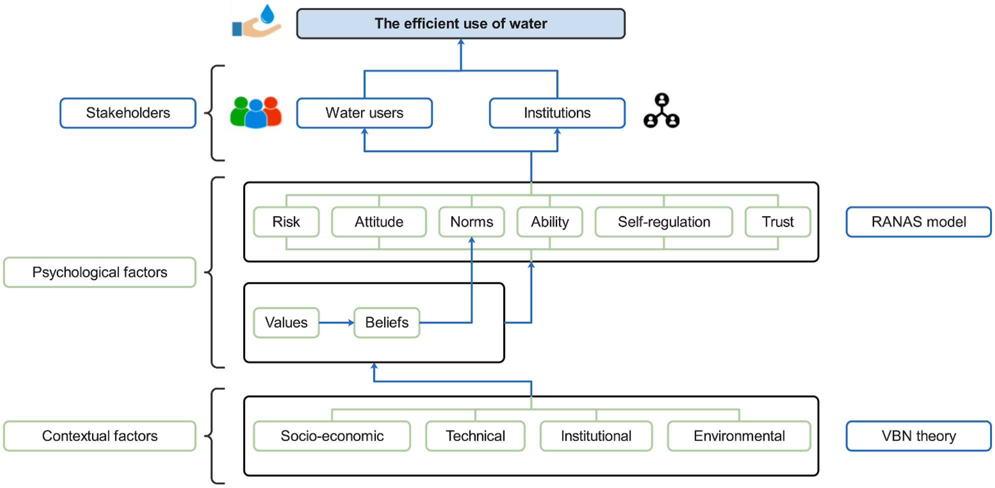

Figure 4.11 A conceptual model integrating behavioral theories to understand efficient use of water. *Adapted from Callejas Moncaleano et al. (2021).*

have been made in global hydrological and human system modeling. The spatial extents of hydrological models of mass and energy balances now span global scales.

Global hydrological models have also been coupled with general equilibrium models to assess supply, demand, and agricultural trade. At the global scale, the trade, prices, and production of agricultural goods and water use can be endogenous. Macroeconomic models study the dynamics of aggregate quantities such as production of goods and services, prices, income, and employment. Agents in the model are economic sectors, government, and families (one agent per country/region, depending on the level of detail offered by the model), whose behaviors are calibrated from secondary data sources (for example, consumption and expenditures of the actors). The most frequently used macroeconomic models in the study of water resources are input-output models (Koks et al., 2015) and computable general equilibrium (CGE) models (Hertel & Liu, 2016). CGE models, because they model national to regional economies including reasonable details of their various sectors, have been extensively used to explore limits to growth, including representations of price-mediated adjustment mechanisms that the world system dynamics model of Meadows et al. (1972) lacked. Extended versions of such models with more complex biophysical relationships and roles of technological changes, population growth, and land cover/land use change in deciphering limits to growth, later emerged in the form of integrated assessment models (IAMs) (Fischer & O'Neill, 2005).

These integrated modeling frameworks of climate, hydrological, biophysical, and socio-economic systems (such as GCAM) provide regional to global perspectives in the context of regional earth system modeling (Liu et al., 2015). As Fig. 4.12 shows, the integration is brought about by incorporating nexus-based constraints within the water, land, climate, and economic-energy system into an integrated model framework. The model identifies trade-offs and win-win situations based on the synergies between these dimensions. The simulated supplies of resources are often linked between biophysical models and economic-energy system models under downscaled climate change scenarios (Dolan et al., 2021). The aggregated supply of resources constrains the simulation of mitigation scenarios with the economic-energy system models since it influences the productivity of various land cover types that the model considers in simulating the scenarios. While the simulated mitigation/adaptation scenarios prescribe the land cover and water demands for the biophysical models, biophysical models and water management strategies in turn define the constraints defining whether the prescribed land cover changes and water availability are indeed feasible.

4.6 Method evaluation

Step seven of Sivapalan and Blöschl's (2015) stepwise approach includes evaluation which depends on study purpose in practical and scientific settings. In modeling, there is often a strong focus on evaluating the fitness for purpose (Hamilton et al., 2022), limits of

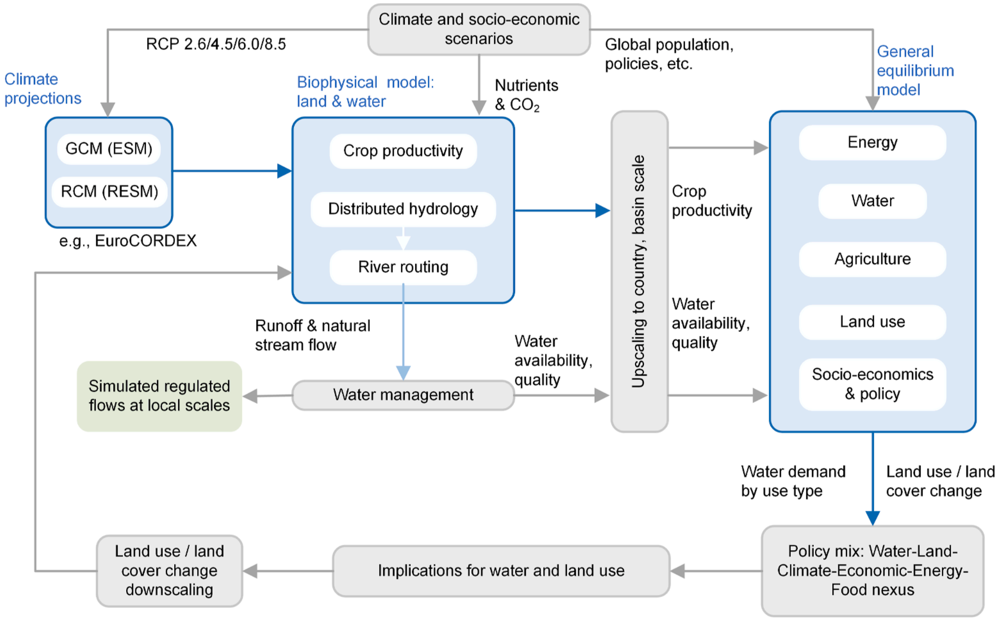

Figure 4.12 An example of an integrated assessment model that integrates large-scale economic, hydrological, and climate models to assess the water-energy-food nexus. Blue items indicate biophysical model outputs; gray items mean socio-economic modeling/scenarios and policy; green items denote integrated model simulations.

acceptability, and limits of applicability. Hamilton et al. (2019) provide a framework synthesizing 32 criteria for model evaluation considering project and system-level outcomes, multi-dimensional and multi-perspective approaches, and process outcome orientations. Based on a meta-analysis of evaluating participation in water resource management, Carr et al. (2012) noted that an intermediate step (intermediary outcome evaluation) has been given less attention than process-oriented and outcome-oriented evaluation, but can identify some real achievements of projects.

A holistic view that includes evaluation of the research design, data collection, and the model is particularly important in the context of human-water relations. Therefore, in addition to accuracy, consistency, and generalizability relevant to quantitative models, perspective, authenticity, and trustworthiness relevant to qualitative models must be considered. Here, we discuss legitimacy and evaluation of processes, empirical evaluation, and uncertainty evaluation.

4.6.1 Legitimacy and process evaluation

The social context of all sciences is increasingly recognized (Saltelli et al., 2020), including issues such as the ethics involved in quantification (Saltelli & Di Fiore, 2020). The starting point for evaluation in studies of change in hydrology and society is therefore in establishing legitimacy of the work and the processes involved (e.g., van Voorn et al., 2016).

When conducting interviews, it is acknowledged that the participant's response cannot be separated from the interview situation and the influence of the interviewer. While contextual factors mean that interviews may not be completely replicable, it is important that they be clearly documented to provide transparency and reproducibility of the protocol. All studies—not just those using interviews—should reflect on the potential influence of the "positionality" of the researcher, i.e., their own identity and background (Rangecroft et al., 2020).

Legitimacy and salience of research may reduce modeling uncertainty, e.g., by focusing only on salient human-water interactions. Novel avenues, such as citizen science platforms, are arising that are filling the gap in informing about human behavior, e.g., with respect to domestic water use when using applications that allow users to document their use. In participatory modeling, the scope for such participation is more interactive than in citizen hydrological data collection, yet more limited in practice. Rangecroft et al. (2018), for example, used a hydrological model to prompt discussions among community members of a village in the Limpopo Basin, South Africa, about future drought impacts, responses, and preparedness. Interesting here is the sequence between qualitative scenario development, quantitative modeling, and qualitative production of future narratives in which the model acted as focal point and stimulus. The "qualification" of model outputs into storylines was an efficient way of dealing with model uncertainties, while the tangibility of the model prediction helped participants to imagine the future.

Stakeholder engagement and participation is therefore a critical part of the modeling process for human-water systems. As highlighted by Melsen et al. (2018), including stakeholders means that modeled relationships and assumptions can be challenged, refined, and ultimately more accurately reflect the reality of how the system is functioning. In research by Carr et al. (2022), stakeholder feedback was gained at several stages of the modeling process to ensure that the model captured the collective perceptions of the system in reality. To support this, the model conceptualization was described pictorially and using straightforward terminology. Additionally, the model may have potential as a tool for shaping stakeholder engagement. For example, it may assist diverse stakeholders to explore necessary trade-offs in the water system, and may structure creative thinking about how different, or new, strategies could be developed and implemented. Shared vision planning developed by the US Army Corps of Engineers has led the way with this approach (Loucks & Van Beek, 2017; Walker et al., 2015).

4.6.2 Empirical evaluation

We use the term "empirical evaluation" to describe any method that involves comparing results with observed behavior of a system or other forms of empirical evidence.

In the context of validating sociohydrological models, comparing the model outputs to a time-series of measured data may be considered to provide a convincing argument for the model's validity. However, time series data of social aspects, such as awareness, memory, willingness, capacity, resilience, etc., rarely exist. Further, datasets of certain variables may be more important than others. For example, Barendrecht et al. (2019) found that data for flood awareness were key to better estimate the parameters of the human-flood system dynamics model for the Dresden floodplain in Germany. This was because the data provided complementary information that was important to identify the parameters of the model, which then enabled the modelers to calibrate it more precisely. Roobavannan et al. (2017b) used complementary sets of variables to calibrate and validate the model for the Murrumbidgee River Basin in Australia, in order to interpret the phenomenon of a pendulum swing in water allocation. The authors used irrigated land area and environmental flow for validation while using flow records at various gauge stations, in addition to labor and population time series, of the basin for calibration. Switching between the two combinations for calibration and cross-validation also provided an assessment of the calibrated parameters. However, similar to Barendrecht et al. (2019), they also found community sensitivity to be a "difficult" variable to model—highlighting the need for greater investigation and exploration of different proxy datasets that will advance understanding of the nature of that variable. The data challenges have been partly ameliorated by incorporating qualitative data from focus groups and narratives, which also help in identifying phenomena (Bou Nassar et al., 2021; Leong, 2018). Recent social media analysis, regular social surveys, and newspaper analysis, combined with data mining advances, have made it possible to infer aspects related to changes in community sensitivity over time (see, e.g., Roobavannan et al., 2018; Wei et al., 2017).

Human-water systems research to date has shown that observed system dynamics can be reproduced by models, even if it can be difficult to replicate the exact values (e.g., Carr et al., 2022; Kuil et al., 2019).

The focus is therefore on generating models in which we are confident that the modeled relationships and outcomes reflect the system dynamics occurring in reality, with which we can reproduce observed dynamics in comparative case studies, i.e., we validate by testing that we are capturing the processes correctly for the right reasons (Senge & Forrester, 1980).

It is important to highlight that models provide only one possible representation of reality (Oreskes et al., 1994). They need to be tested so as to build confidence in the translation of inference from any modeled relationships to reality (Senge & Forrester, 1980; Swaninger & Groesser, 2006). Validation in this sense is an ongoing process that is not only critical for any one model's development but also draws attention to the model's value as an analytical and policy development tool.

4.6.3 Uncertainty evaluation

Beyond building confidence in a method, model, or results, it is common for multiple explanations of a phenomenon to remain, which can be addressed by characterization and evaluation of uncertainty. Evaluation of the models in terms of their structural and parameter uncertainty and potential for error propagation is a critical step in order to make assessments on the reliability of their outcomes and capacity for extrapolating relationships and behaviors from one time and place to another and under different boundary conditions (Rounsevell et al., 2021) (Fig. 4.13). A wide range of methods can be used to explore alternative conceptualizations or models of a system and their implications (Guillaume et al., 2015, 2016).

It is noteworthy that, while modeling and scenario uncertainty analyses are common in natural and water systems research through comprehensive ensemble experiments, these approaches are less common in human systems research. In fact, most uncertainty assessment initiatives have been for natural systems—human systems typically appeared as forcings or scenarios.

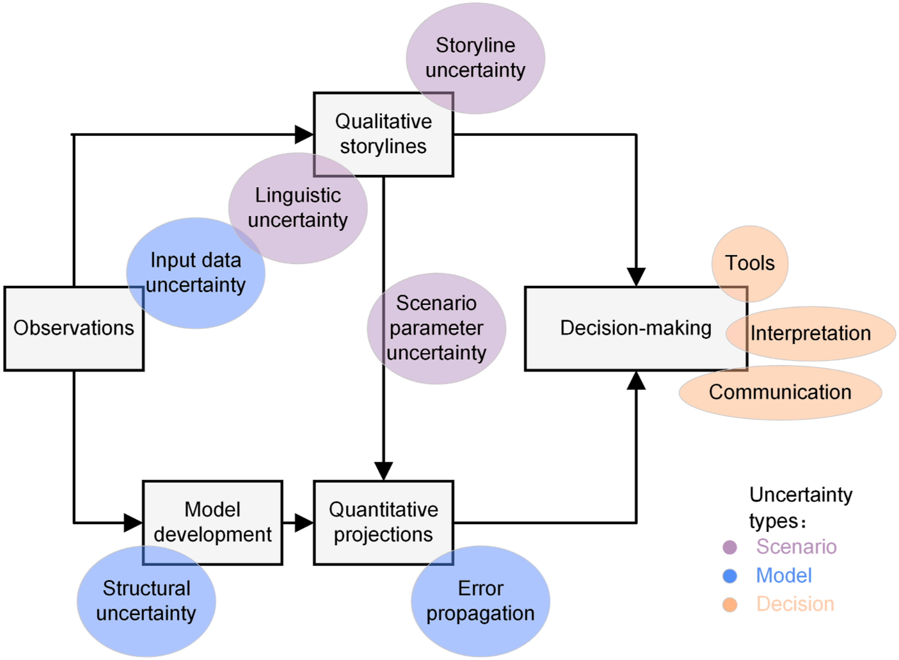

Figure 4.13 Sources of uncertainty in scenarios and models of socio-ecological systems within the context of decision-making. *Adapted from Rounsevell et al. (2021).*

4.7 Challenges and future work

Upon reviewing the prevalent methods of studying human-water relations along the qualitative-quantitative spectrum (Section 4.2.2), we have outlined a methodology where quantitative and qualitative methods can come together around a central quantitative framing. The mixing of methods following this methodology, however, will not be without tensions. In this section, we summarize these discussions under four themes and suggest ways of nudging the methodological tensions toward a productive middle ground for an enhanced understanding of human-water relations.

4.7.1 How to transfer place-based accounts of human-water relations

Many of the qualitative methods reviewed in this chapter are place-based, meaning their results are tied to local contexts with little ambition to generalize. For many of the quantitative methods, especially the modeling methods reviewed, their envisioned reach remains unclear. This brings back a long-standing discussion in hydrology and water resources as to whether or not models, even if they claim to represent universal principles, are essentially place-based because of the effective nature of model processes and parameters at the scale of spatial and temporal discretization (Beven, 2000). Having this discussion is all the more important as hydrological and social processes are being combined in models. It seems that quantitative methods and models are, with their lack of generalizability, not so different from qualitative approaches that are decidedly not about universal principles in the first place.

This said, the discussion of the reach of methods can be enriched through considering to what extent results from place-based analyses, even if they may not be wholly generalizable, may be transferable. Transferability in the context of qualitative methods means the identification of hypotheses or models from cases that can invite questions and ways to think through other cases. In terms of Guba and Lincoln's evaluative criteria (1989), transferability is showing that the findings are applicable to other contexts. In this sense, many qualitative studies cannot be generalized, but they can be applicable. Bringing this consideration into the discussion of quantitative methods and models can enrich understanding of the reach of methodologies such as those envisioned in Sections 4.2 and 4.3.

4.7.2 How to account for social heterogeneity and power dynamics?

A point of criticism of the studies of coupled human-water systems has been the lack of consideration of social heterogeneity and power dynamics. We have seen a few studies focusing on social and behavioral heterogeneity and power dynamics in Panta Rhei (e.g., Chen et al., 2016; Haeffner et al., 2017; Komakech et al., 2012; Lebek et al., 2021; Mukherjee, 2020; Savelli et al., 2021; Thaler, 2021), and this seems to be a promising emergent research field as it builds bridges to connect various disciplines such as hydrology, sociology, anthropology, political science, and human geography.

Further research is needed to better understand how human-water models can better account for intersectional social power dynamics, heterogeneity of preferences (e.g., risk aversion, propensity to change; Montanari et al., 2013; Franceschinis et al., 2021), and preference dynamics (Mason et al., 2018). There are mathematical interpretations of these considerations from the control systems community that deserves further elaboration, especially with respect to embedded power dynamics.

4.7.3 How to advance model calibration, data assimilation, and structure deficiency assessment?

Given that quantitative models of human-water relations have until now been used more to simulate patterns and broad trends rather than actual data series, we see innovation potential in connecting established and novel methods of data assimilation (e.g., Sawada & Hanazaki, 2020), parameter calibration (e.g., Barendrecht et al., 2018), and model structural diagnostics to those models. To this end, the community can draw from the rich tradition of uncertainty analysis in hydrology.

Recent advances in machine learning hold the potential for inferring actors' value functions from observed patterns of decisions in automatic ways (e.g., inverse reinforcement learning) or transferring the information from similar behavioral contexts (i.e., value function transfer). For example, Likmeta et al. (2021) inferred the value function of the dam operator for Lake Como directly from time series of observed release and, for the same system, Canonaco et al. (2021) demonstrated a utility transfer technique to reconstruct the Lake Como operator utility function from similar case studies where those functions are known. Likewise, advances in information theory hold the potential for top-down model development (e.g., via maximum entropy), causal inference, and model evaluation (Kumar & Gupta, 2020).

4.7.4 How to integrate qualitative and quantitative methods?

Qualitative and quantitative data and analysis methods, when employed in conjunction, can reveal different facets of human-water relations—different colors as illustrated by the prism image of Fig. 4.1. In Section 4.2, we offered a methodology centered on quantitative analysis, where qualitative analysis plays a supporting role in conceptualizing and validating system properties. An alternative framing of how quantitative and qualitative enquiry can come together was proposed by Massuel et al. (2018), who describe framing as a process of negotiation between different methods about how to interpret the phenomenon at hand rather than as a process of integration. This negotiation, as the authors argue, is aided by a shared field-based experience of the researchers involved. By extension, this negotiation can also involve actors other than academics and technical experts in line with the participation tradition, discussed in Section 4.3.

In such constellations, for those engaged in quantitative modeling, the value of qualitative data and analysis has been recognized, for example, for building causal loop diagrams, storylines for conceptualizing agent behavior, and for generating data on social processes that are otherwise hard to come by (see Sections 4.2 and 4.3). In contrast, we know much less about how social scientists involved in such endeavors value quantitative models as stimuli for qualitative research. For some constellations of qualitative and quantitative methods, the mutual benefits are straightforward. Lebek and Krueger (2023) conducted ethnographic fieldwork in rural South Africa to create a household survey for statistical modeling. The statistical modeling, in turn, yielded unexpected associations between variables that generated new hypotheses to be investigated ethnographically again in the field. We believe that mixed methods research should go beyond examples like this to probe the value of quantitative methods for qualitative inquiry. Experience from participatory modeling suggests that models can be useful boundary objects for collective sense making of complex situations and envisioning possible futures. Hence, we would expect them to provide useful stimuli for qualitative data collection and analysis as well.

4.8 Summary of key points

- Sociohydrological phenomena can be analyzed in seven steps: phenomenon/domain/scales, conceptual model, variable choice, causal factors, functional relationships, parameter estimation, and model validation. This method is not linear but iterative, with the possibility of returning from Step 7 to Step 1. Qualitative methods may selectively skip and emphasize specific steps.
- The seven-step method can lead to a quantitative sociohydrological model or to qualitative understanding of the system functioning. This adaptability is valuable in addressing the complex dynamics of human-water interactions, accommodating diverse research goals and methodological preferences.
- A variety of approaches can be utilized for the analysis of human-water systems that span the qualitative-quantitative spectrum, from ethnography to IAMs, underscoring the need for multiple perspectives to understand complex phenomena. Combining quantitative natural science methods and qualitative social science methods provides a more comprehensive picture of system functioning than one method alone.
- A participatory approach involving stakeholders enriches research design with credibility. Qualitative data-collection methods, like participant observation, interviews, focus groups, and text-based material coding, are applicable at smaller spatial scales (individuals to communities), while surveys extend to larger scales (individuals to basin-level assessments), closely intertwined with the research process.

- Models are valuable tools for quantitative analysis of phenomena and assessing system functionality. System dynamics models dissect dynamics of complex systems over time in a lumped manner, revealing relationships and feedback. ABMs address heterogeneity of agents and can also offer spatial heterogeneity.
- In the intricate realm of human-water relations, holistic assessment is crucial, especially when data are limited. A comprehensive evaluation should be conducted across the methodological spectrum, ranging from research design to data collection, analysis, and modeling.

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