Chapter 20
Navigating Deep Uncertainty in Complex Human–Water Systems

C. D. Pérez-Blanco

Abstract Complex human–water systems are deeply uncertain. Policymakers are not aware of all possible futures (deep uncertainty type 2), while the probability of those futures that can be identified ex-ante is typically unknown (deep uncertainty type 1). In this context, standard decision-making based on a complete probabilistic description of future conditions and optimization of expected performance is no longer appropriate; instead, priority should be given to robustness, through the identification of policies that are (i) insensitive to foreseeable changes in future conditions (classical robustness that addresses deep uncertainty type 1) and (ii) adaptive to unforeseen contingencies (adaptive robustness that addresses deep uncertainty type 2). This research surveys recent advances in (socio-)hydrology and (institutional) economics toward robust decision-making. Despite significant progress, integration among disciplines remains weak and allows only for a fractioned understanding and partial representation of uncertainty. To bridge this gap, I will argue that science needs to further underpin the development and integration of two pieces of ex-ante information: (1) a modeling hierarchy of human–water systems to assess policy performance under alternative scenarios and model settings, so as to navigate deep uncertainty type 1 and (2) a longitudinal accounting and analysis of public transaction costs to navigate deep uncertainty type 2.

Keywords Deep uncertainty · Socio-hydrology · Robustness

Introduction

Climate change, population growth and changing distributions of wealth will lead water demand to outstrip supply by 40% in 2030, causing GDP growth to decline by as much as 6% in water-scarce areas (i.e. continued negative growth) (World Bank 2016). At the other extreme, floods represent the most economically damaging risk, costing circa $100 billion annually, and their impact is expected to rise to

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$521 billion/year in 2030 (World Resources Institute 2019). The combined effects of growing water scarcity and flood risk increasingly constrain decision-makers to adopt new approaches and policies to the management of the human-modified water cycle. *Critically*, the dynamics of complex human–water systems of relevance for water policy design and implementation are characterized by positive feedbacks, non-mechanistic dynamics and multiple equilibria leading to Knightian or **deep uncertainty**, where it is not possible to identify all possible futures (deep uncertainty type 2) or assign a probability to each identified possible future (deep uncertainty type 1). Under deep uncertainty, standard decision-making based on a complete probabilistic description of future conditions and optimization of expected performance is no longer appropriate; instead, **priority should be given to robustness**, through: (i) the avoidance of policies leading to unfavorable contingencies that can be identified beforehand (classical robustness, which addresses deep uncertainty type 1) (Marchau et al. 2019) and (ii) the avoidance of path-dependent trajectories, so to enable future adaptation to unpredictable, surprising, and potentially catastrophic ("black swan") events that are explainable only after they happen (adaptive robustness, which addresses deep uncertainty type 2) (Garrick 2015).

This research surveys recent advances in (socio-)hydrology and (institutional) economics that contribute toward uncertainty sampling and robust decision-making. I will argue that despite significant progress, integration among disciplines remains weak and allows only for fractioned understanding and partial representation of uncertainty. To bridge this gap, along these pages, I develop a research agenda toward an interdisciplinary, replicable, and scalable research framework integrating data and methods from (socio-)hydrology and economics to *quantify* the broad socioeconomic and environmental implications of adaptation policies in complex human–water systems, and the uncertainty involved in the process, so to allow stakeholders to explicitly trade-off incremental changes in robustness with expected policy performance (e.g. cost-effectiveness). To this end, I argue that science needs to further underpin the development and integration of two pieces of ex-ante information: (1) a modeling hierarchy of human–water systems to assess policy performance under alternative scenarios and models/model settings, so as to navigate deep uncertainty type 1 and (2) a longitudinal accounting and analysis of public transaction costs from before the project or policy commences. Public transaction costs are the institutional and organizational investments required to arrange, monitor, and enforce a policy and are instrumental to *measure* institutions' adaptive ability, avoid path dependent and potentially irreversible trajectories and strengthen adaptive robustness that addresses deep uncertainty type 2. Note that the first piece of information is only partially addressed in the scientific literature, which appears biased toward consolidative modeling and standard decision-making (Marchau et al. 2019); while empirical longitudinal assessments on public transaction costs are "virtually non-existent" (Loch and Gregg 2018).

Building a framework that addresses these gaps is challenging, but now feasible due to: (1) recent growth in availability of data from hydrology and socioeconomic domains (e.g. micro- and macro-economic); (2) recent advances in computational and statistical techniques for processing and harmonizing big data; (3) the growing number of water policy reforms, which can serve as 'living laboratories' for the collection, measurement, and analysis of public transaction costs (Garrick 2015); and (4) the consolidation of analytical and modeling methods proposed by emerging water resource research literature to study impacts and adaptation, including alongside stakeholders (Marchau et al. 2019).

Navigating Deep Uncertainty Type 1: Modular Hierarchies for Multi-system Ensembles

Three fundamental sources of deep uncertainty type 1 can be distinguished: (1) uncertainty arising from scenario assumptions and design (Marchau et al. 2019); (2) "parameter and structural uncertainties" within models (Tebaldi and Knutti 2007); and (3) uncertainty arising from the missing or "overly simplistic" representation of the interconnected dynamics of complex adaptive human–water systems (Pande and Sivapalan 2017).

The first two sources of uncertainty have been addressed with relative success. The Society for Decision Making under Deep Uncertainty has developed tools to address uncertainty arising from scenario assumptions and design through an exploratory modeling approach. Exploratory modeling and analysis works as a prosthesis for the intellect, using computational experiments representing the consequences of alternative sets of feasible assumptions to discover the implications of a priori knowledge—including domains of previously unforeseen contingencies. This information can then be used to illustrate relevant tradeoffs and revise scenarios and policy adoption in successive iterations leveraging on stakeholder and expert feedback until a robust policy is agreed upon (Marchau et al. 2019).

An ensemble of models can be used to sample uncertainty arising from parameter and structural uncertainties. Economic and hydrologic sciences have been successful at developing scientifically sound conceptual models capable of representing the essence of critical systems within the human–water conundrum. These include microeconomic models to represent the behavior of individuals or firms, macroeconomic models to study interrelations among sectors and regions of the economy and their impact on aggregated indicators and hydrologic models to study the movement, distribution, and quality of water at different scales, among other modeling families. There is consensus in the literature that the combination of scientifically sound prediction methods in perturbed physics and multi-model ensemble experiments (i.e. grouping multiple models and exploring alternative values for critical parameters) can be used to sample parameter and structural uncertainties through the ensemble spread. This approach has been already used in disciplines such as climate sciences, economics, and hydrology, also in combination with exploratory modeling (which in climate ensemble experiments are treated as an additional layer to the ensemble referred to as 'initial condition ensemble') (Tebaldi and Knutti 2007).

However, economics and hydrology have not been successful at integrating human and water systems (Pande and Sivapalan 2017). Conventional hydrologic (economic) models perceive pressures from human (water) systems, if considered at all, as external forcings. Where socioeconomic and hydrologic models interact in hydroeconomic models, responses to policy shocks or other *stimuli* are typically assessed using an external economic sub-model, which is subsequently integrated with the architecture of the hydrologic model through piecewise equations. This offers the advantage of a more straightforward and effective representation of causal relationships and interdependencies, while reducing computational costs since shocks do not require to be represented separately for each sub-model. Yet, such holistic models do not capture the interrelationships or two-way feedbacks between human and water systems that shape adaptive responses (Pande and Sivapalan 2017). As a result, the effects of policy- and climate-induced adaptation and feedback responses between socioeconomic, land surface, and water systems dynamics are still poorly understood.

There is a basic need to better understand the dynamics of complex adaptive human–water systems and to represent them in modeling tools that can be used to effectively inform policymakers. To this end, the transformative discipline of *socio-hydrology* has called for the development of integrated approaches that "explicitly account for the two-way feedbacks between human and water systems" (Sivapalan et al. 2014). Recent socio-hydrology-inspired science has explored feedback responses between human (typically water users) and water systems (Essenfelder et al. 2018). In parallel, economics has also developed new tools to explore feedback responses in complex human–human systems, notably between micro- and macro-economic systems (Parrado et al. 2019). These contributions run standard models at each system level independently in *modules*, which are defined as specialized, self-contained mathematical elements that process information and generate outputs and connect them through sets of *protocols*, which are defined as rules designed to manage interrelationships (e.g. two-way feedbacks) between systems' modules (Csete and Doyle 2002). Modularity offers potentially higher detail in the representation of each system, which can be independently developed and adjusted. This makes possible the addition of non-linearity to each element of the system, so that surprises are not so surprising and can be adequately understood, and their repercussions transferred from one system to another.

While holistic models that use differential equations to capture as many systems as possible in comprehensive numerical models have significant practical value and continuing increases in computational power means, they can be systematically upgraded and adjusted to more accurately represent observed responses in human–water systems, it is reasonable to say that "we typically gain some understanding of a complex system by relating its behavior to that of other, especially simpler, systems" (Held 2005). It is through hierarchies of systems of increasing complexity, amenable to experimental manipulation that experimental sciences such as biology have made steady progress in, e.g., deciphering the human genome. Recently, climate research has put a stronger emphasis on model hierarchies as a means to link the complexity of high-end holistic simulations with a deeper understanding of the processes at work provided by conceptual models, so to discover previously unaccounted futures and explore their implied consequences. Analogously, to the extent that we can divide complex human–water systems into components that can be tested and developed in isolation, a hierarchy of human and water systems would make possible a more comprehensive understanding of the relevant processes involved through the use of conceptual models that capture their essence, and of the interrelationships among them through layers of feedback protocols (Csete and Doyle 2002).

I argue that recent advances in the construction of protocol-based modular frameworks provide the backbone for the development of interdisciplinary modeling hierarchies that connect multiple systems through two-way feedbacks (*multi-system hierarchy*). Each module within the hierarchy can be populated with multiple models (*multi-model ensemble*) and combined with scenario discovery techniques that explore scenario uncertainty through varying initial states and forcings (e.g. climate change scenarios, policy scenarios). The result is a large database of simulations in which each simulation represents the economic and environmental performance under one specific scenario and modeling setting. This information can be used to identify futures where proposed policies meet or miss their objectives, explore potential tipping points, and inform the development of robust policies that show a satisfactory performance under most conceivable futures.

Navigating Deep Uncertainty Type 2: Measuring and Understanding Transaction Costs to Avoid Techno-Institutional Lock-In

Assume the complete set of future outcomes in a system is R_A, where outcomes represent an event plus the policy response to that event. Through modeling we can reveal a fraction of the complete set $(R_A - r_\mathrm{A})$, where $r_\mathrm{A} = (\varepsilon_{1\mathrm{A}} + \varepsilon_{2\mathrm{A}})$, ε_1 is modeling limitations and ε_2 represents unawareness (the consequence of a priori unknowns). In coupled modeling frameworks, the second model or group of models in the hierarchy will then begin searching the repercussions of the feasible set $(R_A - r_\mathrm{A})$ in a related system B and assess relevant feedbacks. Due to model limitations and unawareness, the coupled modeling framework will yield an incomplete set of future outcomes $(R - r_A * r_B)$, where R is the complete set of future outcomes in the coupled system and $r_B = (\varepsilon_{1B} + \varepsilon_{2B})$. Note again that by adding systems to the ensemble, modeling limitations and unawareness at each system level compound, increasing the range of possible future outcomes that we are unable to foresee. We can explore ways to limit the impact of ε_1 by adding and better representing models and scenarios across systems. This is indeed the objective of combining modular hierarchies with exploratory modeling and ensemble experiments. *However, ε_2 will persist until empirically revealed*. This is deep uncertainty type 2.

Deep uncertainty type 2 is the consequence of "limits in the knowledge base, chaotic dynamics, future actions by decision-makers, inherent randomness, non-stationarity and changes in societal perspectives and preferences over time", including stakeholders' preferences and their assessment of policies (Walker et al. 2003). Under deep uncertainty type 2, the only thing we know is that we do not know. Future predictions are "impossible", and society finds itself exposed to surprises, some of them potentially catastrophic ("black swans") (Taleb 2008). The natural question that follows is what can be done where the only thing we know is that we do not know. Critically, deep uncertainty type 2 is not an extreme on the scale of uncertainty—that place is reserved to *total ignorance* (Walker et al. 2003). Knowing we do not know gives us a valuable piece of information and allows us to plan in advance.

In addressing deep uncertainty type 2, the challenge is to strengthen **adaptive robustness** (Garrick 2015). Adaptive robustness involves the removal of techno-institutional barriers that constrain our ability to take corrective action so that incumbent policies can be replaced by superior alternatives as new information on possible futures is made available through the occurrence of surprises. Measuring and understanding techno-institutional barriers require information on *public transaction costs*, the institutional and organizational investments required to arrange, monitor, and enforce a policy. Public transaction costs include: (1) administering, monitoring, contracting, and enforcing current policy arrangements (termed *static transaction costs*) and (2) periodically designing, enabling, implementing new and/or transitioning existing management arrangements (termed *transition costs*). Transaction cost investments are also affected by (3) previous policy or institutional choices, which may enhance or constrain future selections (termed *technological and institutional lock-in* costs) (Loch and Gregg 2018).

Since predictions of future transaction costs are impossible under deep uncertainty type 2, anticipating the emergence of adaptively robust institutions is challenging. Yet, past transaction costs can be used to draw valuable insights into the trends and future development of adaptively robust institutions. The concept of *adaptive efficiency* is particularly useful in this regard. Adaptive efficiency measures the capacity of institutions to achieve economic efficiency over the long term. As compared with the conventional neoclassical approach, which views institutions as static and exogenous constraints within which costs and benefits are assessed, adaptive efficiency aims to understand long-term trajectories of institutional economic performance in contexts of entrenched path dependencies, complexity, uncertainty, and feedback between policy reform and implementation. In other words, adaptively efficient institutions are those showing "capacity to solve evolving and complex dilemmas over long periods of time, in a context of uncertainty and periodic, often unforeseen, shocks" (Garrick 2015). Note that **the concept of adaptive efficiency mirrors that of adaptive robustness**: adaptive efficiency looks at past institutional performance to individuate those institutions that were successful and efficient in taking corrective action; and adaptive robustness aims to remove constraints to the institutional ability to take corrective action in the future, so that future institutions are adaptively efficient. While ex-post adaptive efficiency does not equate to adaptive robustness, it is reasonable to expect that institutions that have proven to be adaptively efficient over long periods of time are more likely to be adaptively robust in the future. After all, the best thing we can do to predict the future is to prognosticate from the past. Just like (paleo)climatic data series can help narrowing the equilibrium response of global surface temperature to alternative CO_2 concentrations in climate models, or past choices are used to reveal agent's preferences and predict future behavior in economic models, data on past techno-institutional performance over sufficiently long periods of time can give valuable information to assess whether we are investing in institutions that are adaptively robust.

Garrick (2015) associates adaptive efficiency with "three performance indicators: (1) how well the objective(s) have been met (i.e. effectiveness); (2) the average public transaction costs per unit of the met objective(s); and (3) total program budgets". For an adaptively efficient institutional complex, these three performance targets should be "increasing, decreasing and sufficient", respectively (Garrick 2015). Although these three indicators are empirically measurable, public transaction costs are typically excluded from performance assessments of water or other environmental policies. In fact, transaction costs remain "a black box concept" for researchers, who rarely progress beyond zero transaction costs ideals (Loch and Gregg 2018). Although recent research has monetized transaction costs of water policy reform in South Africa, USA, and Australia, **the empirical base on transaction costs of water policy reform elsewhere is virtually non-existent**. **Moreover, in those areas where transaction cost data are available, studies usually do not quantify them over time** (Loch and Gregg 2018). Yet, measuring and analyzing adaptive efficiency to understand and predict future institutional performance, and whether it leads toward path-dependent/adaptively robust trajectories, necessitates longitudinal data on transaction costs.

Developing and analyzing longitudinal transaction cost data is in itself a major breakthrough that will help us understand the emergence of path-dependent/adaptively robust trajectories; yet, the natural question that follows is: *what can we do if past institutional performance leads to path-dependent trajectories that constrain our ability to take corrective action?* Existing technologies and institutions can constrain the range of policies that can be adopted in the coming years or decades through institutional and technological lock-in. In the context of water resource management, lock-in refers to the inertia of conventional engineering-based policies due to the mutually reinforcing physical, economic, and social constraints that emerge from existing technologies and institutions. Techno-institutional lock-in dynamics are driven by path-dependent increasing returns to adopted technologies and institutions at different levels: scale economies (production costs per unit decrease as fixed costs spread over growing production), learning economies (costs fall and performance improves as specialized knowledge and skills accumulate through experience), adaptive expectations (increased confidence about quality, performance, and permanence), and network economies (systemic relations among institutions, technologies, infrastructures, suppliers, and users). Water resource management is particularly prone to lock-in of conventional engineering-based policies due to large capital investments and long infrastructure lifetimes. The combined interrelationships between technological systems and basins' institutional matrices typically result in a self-referential system whose value increases with the growth of the techno-institutional complex (Unruh 2000).

The question of how to overcome techno-institutional lock-in in water resources management has received increasing attention in recent years. While traditional neoclassical economics argues that even marginal efficiency improvements are sufficient to drive the adoption of superior policies, empirical studies show that the inertia created within a techno-institutional complex necessitates an order-of-magnitude improvement in economic performance to induce transition, through **exogenous "annealing forces" that give change momentum** (Unruh 2000). Such an improvement is unlikely to arise endogenously from the techno-institutional complex. Public institutions typically show patterns characterized by incremental change, rather than transformational, over long periods, while examples of technology-led transformational responses are very limited (see below). The endogenous dynamics of a techno-institutional complex tend to create and reinforce its own stability or equilibrium, potentially leading to a path-dependent process of technological and institutional co-evolution that creates barriers to the diffusion of new, transformational policies.

Conclusions and Recommendations

Along these pages, I have surveyed recent advances in (socio-)hydrology and (institutional) economics toward robust decision-making; identified gaps in the development and integration of this research; and suggested a way forward in the integration of data and methods from natural and social sciences, so to deliver a research framework that informs the adoption of robust water policies with higher expected economic and environmental performance. Three major recommendations for future scientific work and research emerge from the analysis:

The development of a flexible and interdisciplinary modular hierarchy for the development of multi-system ensembles that incorporates and assesses the "two-way feedbacks" among modules, so to represent and understand the adaptive behavior of complex human–water systems.

The effort to gather longitudinal transaction cost data to create a database that supports analysis (notably through econometrics) toward a more in-depth understanding of institutional performance and key drivers of adaptive robustness, including "annealing forces" that impulse change and break up from path-dependent trajectories.

The integration of stakeholders in the generation of methods and results, so to underpin the emergence of valuable science-policy synergies that strengthen research quality and help identify statically/dynamically and adaptively robust policies with higher expected economic and environmental performance.

The three innovative elements above provide the pillars for the development of an interdisciplinary, replicable, and scalable research framework that *quantifies*the broad socioeconomic and environmental implications of adaptation policies and the uncertainty involved in the process, so to allow stakeholders to explicitly trade-off incremental increases in static/dynamic and adaptive robustness with expected policy performance, including policy costs, benefits, and effectiveness.

Beyond its scientific merit, the research agenda above have the potential to comprehensively test and demonstrate the performance of alternative solutions to water-related challenges and support decision-making toward the adoption of robust adaptation policies with potential to contribute to water policy objectives. Application of the research framework above will provide new insights for water policy as well as for the broader sphere of sustainable development. Understanding the implications of adaptation in terms of water reallocation and rationing, and related uncertainties, is relevant for policymakers who have committed to the good ecological status of water bodies, and also in terms of policy planning of related economic sectors (e.g. agriculture, agro-industry, tourism) and overall sustainable development, as substantiated in SDG 6 (UN 2015). Policymakers in these spheres need to be aware of trade-offs and distributive implications of adaptation policies in the water sector and below and will benefit from the methodological and empirical insights provided by the research agenda above.

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