The seventh facet of uncertainty: wrong assumptions, unknowns and surprises in the dynamics of human-water systems

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Abstract

The scientific literature has focused on uncertainty as randomness, while limited credit has been given to what we call here the "seventh facet of uncertainty", i.e. lack of knowledge. This paper identifies three types of lack of understanding: (i) *known unknowns*, which are things we know we don't know; (ii) *unknown unknowns*, which are things we don't know we don't know; and (iii) *wrong assumptions*, things we think we know, but we actually don't know. Here we discuss each of these with reference to the study of the dynamics of human-water systems, which is one of the main topics of Panta Rhei, the current scientific decade of the International Association of Hydrological Sciences (IAHS). In the paper, we argue that interdisciplinary studies of socio-hydrological dynamics can help coping with wrong assumptions and known unknowns. Also, being aware of the existence of unknown unknowns and their potential capability to generate surprises or black swans can contribute to more robust decisions in water management and disaster risk reduction.

Keywords: Epistemic uncertainty, Feedbacks, Socio-hydrology, Black swans, Resilience

Introduction

The number seven has been very popular and widely used for a long time: the Seven Deadly Sins, the Seven Wonders of the World, the Seven Hills of Rome, the Seven Dwarves and the much more recent Murakami's Little People of 1Q84. Mandelbrot (1997) introduced the seven states of randomness, and the number seven also has some popularity among hydrological scientists dealing with uncertainty: Pappenberger et al. (2006) discussed seven reasons not to use uncertainty analysis, while Juston et al. (2013) provided seven reasons to be positive about uncertainty.

Uncertainty is usually associated with the throwing of dice, which, strangely enough, have only six (and not seven) facets! A die was used, for instance, as the official logo of the 2013 Leonardo Conference in Kos, Greece, titled "Facets of Uncertainty". We think that this is consciously (or subconsciously) due to the fact that uncertainty is often directly (or indirectly) related to the concepts of randomness and probability.

Sources of uncertainty can be classified in a variety of ways (Knight, 1921; Ferson and Ginzburg, 1996; Apel et al., 2004; Beven, 2012). These classifications enable a better exploration of the different sources of (unreducible or reducible) uncertainty and contribute to explicitly recognize the limitations of our analytical frameworks. It has been showed, for instance, that scientists and experts have a tendency to over-confidence as we tend to grossly underestimate uncertainty (Cooke, 1991; Shlyakhter et al., 1994) across a variety of studies, experts and questions (Lin and Bier, 2008). Differentiating the sources of uncertainty also supports the selection of appropriate methods (e.g. probabilistic or fuzzy) to deal with uncertainty and support the decision making process (Klir, 2006).

In the 1920s, Frank Knight proposed a differentiation between the uncertainties that can be treated as probabilities and what he called the "true uncertainties" that cannot be quantified in probabilistic terms (Knight, 1921). More recently, Ferson and Ginzburg (1996) demonstrated the importance of distinguishing between variability and ignorance as their proper assessment requires different methods. In this paper, we refer to a similar classification, which differentiates between aleatory and epistemic uncertainties (Apel et al., 2004; Beven and Smith, 2014).

Aleatory comes from the Latin *alea*, which means a die or game of dice. Aleatory uncertainty is related to the random variability of processes (Koutsoyiannis, 2010; Montanari and Koutsoyiannis, 2012). Probabilistic methods are valuable tools for dealing with the uncertainty related to chance and randomness, which, at the current time, cannot be reduced by improving our knowledge of the systems through scientific efforts. For instance, flood risk is often estimated by referring to the expected annual flood damage (Arnell, 1989) over long time horizons, such as 20 or 30 years. However, the actual damage (direct and indirect, tangible and intangible; see e.g. Giupponi et al., 2014) of future flood events will significantly depend on unpredictable factors, such as the exact time of the day, and day of the week, when the big, extreme flood event will eventually occur (Di Baldassarre et al., 2009a), e.g. the same event would result into significantly different damages if it occurs on Sunday night during summer or during rush hours on a Friday afternoon. While the exact time of occurrence of future flood events cannot be deterministically predicted, this intrinsic uncertainty can be assumed to be predominantly aleatory and can be easily treated in probabilistic terms.

Epistemic comes from the Greek ἐπιστήμη, which means knowledge. Sources of epistemic uncertainty are related to the lack of knowledge (Beven and Young, 2013). In some instances, we may understand some essential processes and be able to elaborate a number of stylized facts (Kaldor, 1957), but we do not have adequate or sufficient knowledge of all the details needed to properly capture these essential processes into our analytical frameworks.

As epistemic uncertainty is not about the game of dice, here we call it the "seventh facet of uncertainty" and discuss its role in the observation and modelling of human-water systems, which is one of the main topics of Panta Rhei, the new IAHS Scientific Decade dealing with changes in hydrology and society (Montanari et al., 2013). In particular, as social dynamics and their interplay with hydrological changes is largely unknown, and surprises might play a major role, we posit that the study of human-water systems will require going beyond current approaches, whereby epistemic uncertainty is neglected or treated *as if* aleatory, as well as heavy reliance on quantitative predictions.

Our discussion is structured by differentiating three types of lack of understanding, with reference to the study of human-water systems: (i) *known unknowns*, which are things we know we don't know; and (ii) *unknown unknowns*, which are things we don't know we don't know; and (iii) *wrong assumptions*, things we think we know, but we actually don't know.

Human-water systems

Societies strongly rely on access to water resources, which is essential to support livelihoods and provide favourable conditions for socio-economic development (Di Baldassarre et al., 2010a). While benefiting from water services, humans also alter the hydrological regime (Koutsoyiannis et al., 2009; Vörösmarty et al., 2010; Wagener et al., 2010; Lane et al., 2011).

Savenije et al. (2014), for instance, identified four main types of human impacts on hydrology: (i) direct diversion of water flows (water supplies to cities, industries and agriculture), (ii) stream network transformation (construction of dams and reservoirs), (iii) changing river basin characteristics (deforestation, urbanisation, drainage of wet-lands and agricultural practices), and (iv) alteration of the regional or global climate (greenhouse gas emissions and land cover changes).

Hence, as societies change the hydrological regime, hydrological changes simultaneously shape societies. Figure 1 shows the coupled dynamics of hydrology and society driven by global changes in climate, economy, technology and culture.

Fully coupled human-water systems are complex and non-linear. And the dynamic interplay between hydrology and society (Figure 1) is still poorly understood. Thus, the seventh facet of uncertainty plays a major role in the study of dynamic human-water systems, which is the main goal of socio-hydrology (Sivapalan et al., 2012; Srinivasan et al., 2012; Di Baldassarre et al., 2013ab; Montanari et al., 2013).

Recognizing and assessing uncertainty is crucial to provide useful information to decision makers (Pappenberger et al., 2006; Faulkner et al., 2007; Montanari, 2007; Blazkova and Beven, 2009; Koutsoyiannis et al., 2010; Brandimarte and Di Baldassarre, 2012, Beven, 2012; 2014; Krueger et al., 2012; Juston et al., 2013). To this end, a number of probabilistic methods have been developed (e.g. Beven, 2009; Di Baldassarre et al., 2010b; Neal et al., 2013). As they are often based on an (unavoidably) incomplete collection of potential scenarios, the issue of what is exactly meant by probability arises. As a matter of fact, the uncertainty affecting the interconnected dynamics of hydrology and society is much more complex than the probabilities that e.g. gamblers estimate when playing dice or enjoying casinos.

Figure 2 shows examples of ludic, hydrological and socio-hydrological time series whereby the reliability of probabilistic methods decrease as the seventh facet of uncertainty plays an increasingly major role. The first diagram (Figure 2a) is generated by simulating the outcomes of a fair-sided die, which are assumed independent and identically distributed. This is an example of ludic processes. Ludic comes from the *latin ludus*, which means "play or game". Taleb (2007) introduced the term "ludic fallacy" to refer to the misuse of the narrow world of games, casinos and dice (whereby probabilities are known) to simulate the uncertainty of real-world processes. The second time series (Figure 2b) is a long time series of hydrological data, i.e. annual minimum water levels of the River Nile at Roda. Figure 2b shows long duration structure, memory and persistence (Koutsoyiannis and Montanari, 2007, Koutsoyiannis, 2013). Probabilistic methods can still be used to handle this type of uncertainty, but they require the identification of a model of the underlying stochastic structure (Montanari and Koutsoyiannis, 2012). Lastly, the third time series (Figure 2c) refers to the growth and collapse of the Maya civilization. It shows the evolution of the human population over centuries and the potential relations with hydrological conditions. It has been showed, for instance, how technological revolutions triggered population and economic growth in the Maya lowlands, whereas the persistence of drought conditions eventually led to the societal collapse (Haug et al., 2003; Gill et al., 2007). However, it is difficult to rigorously test these causal links because the temporal resolution of human population data reconstructed from archeological records is very coarse (Figure 2b), while the proxies used for dating historical droughts are affected by significant uncertainties (Aimers and Hodell, 2011; see also Yancheva, 2007 and related discussion).

Known unknowns

Major flooding occurred in Brisbane (Australia) in 2011. More than 10,000 properties were affected and 25 people died (Bohensky and Leitch, 2014). This flood disaster was perceived as a surprise by the local population despite the occurrence of major flooding in 1974. People were surprised because, after the 1974 event, a number of flood protection measures were implemented, including the Wivenhoe Dam. The presence of this flood protection structures “led to the popular belief that Brisbane was flood proofed” (Bohensky and Leitch, 2014). Similarly, a few years before in 2005, people in New Orleans were surprised by the catastrophic flooding caused by levée failure during the Katrina event (Kates et al., 2006).

New Orleans and Brisbane are only two recent examples of the so-called levée effect or paradox: that the consequence of building (or strengthening) flood protection measures is that the memory of flooding (and risk awareness) tends to decay over time and therefore more socio-economic development often takes place in flood prone areas. Hence, the reduced probability of flooding might generate increasing potential consequences.

The levée paradox is an example of a known unknown. The paradox was already identified by White (1945) and has been discussed by several authors (Kates et al., 2006; Montz and Tobin, 2008; Di Baldassarre et al., 2009b; Castellarin et al., 2011; Viglione et al., 2014). Most flood scientists know about it. Yet, methods to capture it in the assessment of future flood risk (which can be defined as a combination of flooding probability and potential adverse consequences) are completely lacking. For instance, when flood defense structures are planned and designed, current methods can indeed estimate the corresponding reduction of flooding probability. However, they do not assess how such a reduction might trigger an increase of the adverse consequences of flooding.

This is not a trivial aspect in assessing a realistic flood risk. There is evidence that flood risk might even increase in the long term as a result of flood protection measures (Di Baldassarre et al., 2013a). Thus, while there have been an enormous development of rigorous, formal, probabilistic methods to estimate uncertainty in flood hazard assessment, we still lack fundamental understanding of how flood risk actually evolves in time. It is bizarre that we provide estimates of future flood hazard with sophisticated uncertainty bounds, while neglecting crucial aspects (such the levée effect) that might determine if flood risk will actually increase or decrease!

Other examples of known unknowns are the spontaneous adaptation of human societies to changing environments. For instance, there is empirical evidence that flood damages are lower when a flood event occurs shortly after a similar one. Wind et al. (1999) showed that the losses caused by the 1995 flood at the Meuse River were much lower than those caused by a previous event, of similar magnitude, that occurred in 1993. Similarly to the levée effect, this process of human adaptation effect, or learning processes, cannot be captured by the current methods of flood risk assessment. Mechler and Bouwer (2014) recently showed similar spontaneous dynamics with reference to Bangladesh, and demonstrated the limitations of our analytical frameworks in projecting future disaster risk.

Moreover, many puzzles encountered in dealing with water sustainability challenges are caused by our inadequate explanatory power (e.g. water trade paradox, efficiency paradox, peak-water water; see discussion in Sivapalan et al., 2014) of feedbacks between social and hydrological processes. These effects are not mere paradoxes or exceptions. They actually drive the dynamics of many human-water systems (Di Baldassarre et al., 2013ab; Sivapalan et al., 2014).

Sometimes, experts argue that these paradoxes are caused by irrational human behavior, or mismanagement. But, our point is that the study of human-water systems should first aim to understand and simulate how the human-water systems actually work, including spontaneous social dynamics, informalities, values and norms.

Historical analyses of human-water interactions over long time scales, i.e. centuries, can be very challenging. The aforementioned example of the collapse of the Maya civilization shows the issues encountered when dealing with long time series of archeological data (human population, Figure 2c) and proxies of historical climate conditions: causality links between social and hydrological dynamics are difficult to test (Yancheva, 2007; Aimers and Hodell, 2011). Nevertheless, empirical studies of human-water interactions at time scales relevant for water management and disaster risk reduction, i.e. years to decades, can be much more feasible. Urbanized deltas and floodplains, for instance, are examples of ideal laboratories for the (inter- or trans-disciplinary) study of the interplay between social and hydrological processes as the interactions between human and water systems are apparent and have relevant impacts (Di Baldassarre et al., 2013a). In these flood-prone areas, human settlements, flood control measures, and memory of flooding have gradually co-evolved at similar temporal (years to decades) and spatial (floodplain) scales, while they have been also significantly affected by the sudden and localized occurrence of flooding events.

Long time series of demographic, economic and hydrological data along with information about human adjustments to floods are already available for many case studies, such as New Orleans, the Tiber in Rome, and the Dutch delta (Werner and McNamara, 2007; Aldrete, 2007; de Moel et al., 2011). Yet, to understand the dynamics emerging from the poorly explored interactions and feedbacks between human and water systems, there is a need to start collecting more empirical evidence. Socio-hydrological models (Di Baldassarre et al., 2013b, Viglione et al., 2014) can provide insights about the type of data that we need to collect to observe the dynamic interplay between physical and social processes. Hence, we think that more observations and empirical studies can significantly contribute to a better understanding of the dynamics of human-water systems and therefore reduce this type of epistemic uncertainty.

Unknown unknowns

The study of human-water systems requires an explicit treatment of the interplay between social physical processes. In this context, besides the aforementioned paradoxes that urge more understanding, there are many other things we don't even know we don't know (as stated by Donald Rumsfeld in February 2002). Some of these unknown unknowns may occasionally result in the so-called "black swans": unexpected events with an extremely high impact on the system, which are essentially impossible to forecast. Yet, after their occurrence we will usually attempt to rationalize and explain them (Taleb, 2013). These unexpected events are typically created by unique, unrepeatable combinations of contexts and cascades of contingencies. However, after they occur, humans tend to over-react and over-estimate their probability, potentially leading to some unintended consequences.

While, as discussed above, more interdisciplinary research exploring the dynamics of human-water systems can help reducing the epistemic uncertainty related to known unknowns, there is nothing we can do about unknown unknowns as we don't even know what we don't know. However, being aware of their potential occurrence is crucial as it supports the process of water management and disaster risk reduction. In this sense, black swans remind us about the importance of reducing the negative impacts of unexpected events, rather than focusing only on the precise (but most likely inaccurate) estimation of their close-to-zero probability (Makridakis and Taleb, 2009ab). Decreasing the potential adverse consequences of water-related disasters by enhancing the resilience (and reducing the vulnerability) of human societies, can be more robust than heavily relying on predictions of the close-to-zero (but essentially unknown) probability of water-related disasters caused by unrepeatable combinations of contexts and cascades of contingencies. For instance, improving evacuation and contingency plans does not necessarily require an accurate and precise estimation of probabilities, but it can significantly increase the resilience of human-water systems, i.e. the ability to recover after an event.

Thus, potential surprises and black swans suggest the need to go beyond heavy reliance on predictions, and traditional top-down approaches based on probabilistic assessments of hydrological hazards. In this context, Blöschl et al. (2013) comprehensively discussed the potentialities of complementing traditional top-down approaches with bottom-up ones. Bottom-up approaches do not start from probabilistic prediction, but, rather, from the societal and economical vulnerability of communities and individuals and explore the possibilities (rather than the probabilities) of failures by explicitly considering the expertise of local stakeholders and risk managers (see e.g. Lane et al., 2011). For instance, Wilby and Dessai (2010) showed how the vulnerability of the human-water systems to droughts and water scarcity can be reduced by enhancing the connectivity of water supply infrastructures and making abstraction licenses time-limited. While this combination of measures could not be considered "optimal", it is more robust than alternative low-regret options to the potential occurrence of unexpected events with potentially devastating consequences. Thus, it is by acting from a vulnerability's viewpoint that water managers and scientists can reduce the negative impacts of unknown unknowns and potential surprises.

Wrong assumptions

Besides unknowns, there are also things we think we know, but we actually don't know. This is what we call here "wrong assumptions". Any scientific work, including hydrological or socio-hydrological studies, is necessarily based on a number of assumptions. Aware of the limitations of our hypotheses, we typically follow a parsimonious approach and focus on the dominant processes that drive the dynamics. However, while some assumptions may work for a number of case studies, they can be significantly wrong in other cases.

To make this point, we introduce two fictitious characters that are inspired by the ludic fallacy (Taleb, 2007). Dr. Maria Smith, graduated summa cum laude at MIT, the youngest professor at Princeton University. She is a "logical positivist". "Smart" Angie, perhaps graduated somehow/somewhere, is a great entrepreneur that got very rich in a few years. She is a "sceptical empiricist".

A test is made. A coin is flipped 99 times, and each time it comes up heads. The two ladies are asked what the odds are that the 100th flip would also come up heads.

Without any hesitation, Dr. Smith says: "Odds are not affected by previous outcomes, so the odds must be 50%!"

Smart Angie thinks about it and eventually says: "Well, if it came up heads 99 times in a row there must be something wrong with this coin! So, odds must be much more than 50%!"

The point made by Smart Angie is that the coin must be loaded. In classical terms, odds of the coin coming up heads 99 times in a row are so low that the *assumption* that the coin had a 50% chance of coming up heads *is most likely wrong*.

Similarly, the occurrence of many 1-in-100 year flood events within a few years may suggest issues with the typical assumption of treating annual maximum flows as time series of independent and identically distributed random variables. Hydrological extremes can be affected by long-term persistence and memory related to climate variability. Bloeschl and Montanari (2010) as well as Hall et al. (2013) showed examples of occurrence of flood-rich and flood-poor periods. Also, by analyzing Figure 2b one can observe alternating cycles of drought-rich periods, whereby annual minimum levels are persistently lower than the average, and drought-poor periods, whereby annual minimum levels are persistently higher than the average.

This an example of the many hypotheses that have become standard and have not been sufficiently challenged (similarly to the way Dr. Smith keeps assuming the coin to be fair). While the assumption of treating hydrological extremes as independent and identically distributed can result acceptable (from a practical viewpoint) in a few instances, this assumption should be tested and not merely be taken for granted. For another hydrological example see the discussion of preferential flows in relation to the transport of phosphorus and pesticides in Beven and Germann (2013).

When it comes to the non-linear dynamics of human-water systems, the issue of making fundamentally wrong assumptions becomes even larger as the perception of hydrological change and attitude towards risk can strongly vary across human societies depending on political and socio-economic conditions as well as cultural values (Kahneman and Tversky, 1979; Thompson et al., 1990; Viglione et al., 2014). And given wrong assumptions, of course, we should expect surprises in the future (as seen also in other disciplines, such as economics).

It should be noted that some wrong assumptions can be related to known unknowns. For instance, while historical changes show that the dynamics of future flood risk can be significantly affected by socio-hydrological feedbacks, such as the levee effect, these feedbacks are, as mentioned above, assumed not to matter in state-of-art assessments of future flood risk. Moreover, some other wrong assumptions can be caused by unknown unknowns and we (might) become aware of their fallacy only after the occurrence of surprises or black swans.

Conclusions

Despite centuries of water management, we still lack the fundamental knowledge of the essential dynamics driving the long term behaviour of human-water systems. Over the past decades, focus has been given to assess in probabilistic terms the uncertainty of the assumed behaviour (how it should work) of the system, rather than exploring ranges of the actual behaviour of the system (how it actually works). This has been related to the focus on uncertainty as randomness along with limited credit to epistemic uncertainty, which we called here the seventh facet of uncertainty.

The increasing impact of human activities on hydrological dynamics, in a time that some calls Anthropocene, has led to a growing interest on the study of water-society interactions. As the dynamics of human-water systems are still largely unknown, and social dynamics are highly unpredictable, we argued that there is a need to go beyond current approaches (focusing on uncertainty as randomness and probabilistic methods) and give more credit to the seventh facet of uncertainty. In particular, we proposed new observations and empirical studies of coupled dynamics of hydrology and societies to increase our knowledge of the behaviour of fully coupled human-water systems and reduce epistemic uncertainty. Hence, scientific understanding is believed to be a way to deal with wrong assumptions and known unknowns in the study of the interplay between social and hydrological processes, which one of the main focuses of Panta Rhei, the current IAHS's scientific decade.

We also discussed that, while unknown unknowns cannot be understood as we don't even know what we don't know, being aware of their existence and their potential capability to generate surprises, can help from a management viewpoint: we cannot predict black swans, but we can act to reduce their adverse consequences.

Acknowledgments

We would like to acknowledge the Guest Editor, Dr. Steven Wejis, and two Anonymous Reviewers for providing constructive comments to our paper. The present work was developed within the framework of the Panta Rhei Research Initiative of the International Association of Hydrological Sciences (IAHS).

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Figures

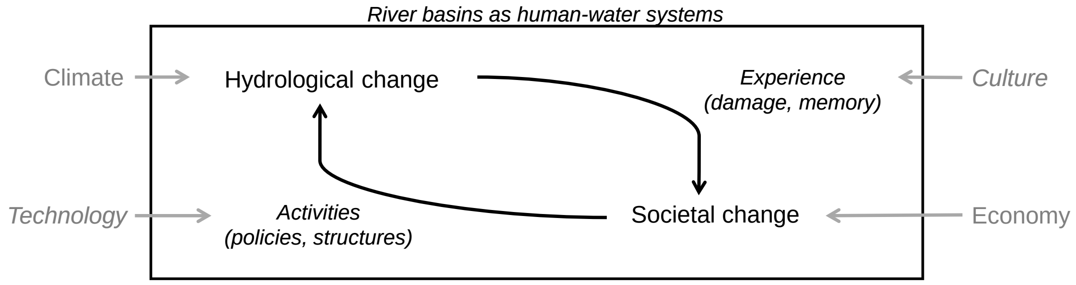
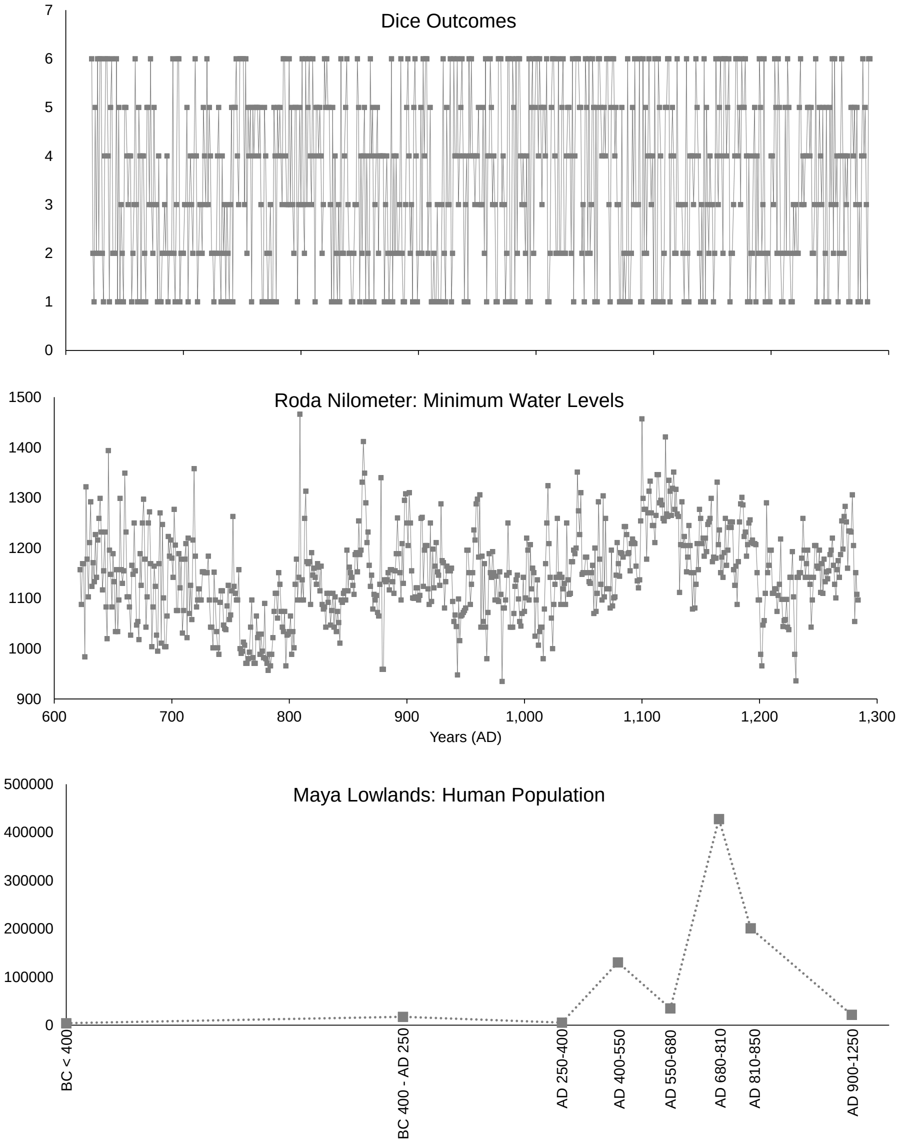


Figure 1. The socio-hydrological cycle: societies change the hydrological regime via human activities, while the experience of hydrological changes shape societies. Human and water systems are deeply intertwined and respond to global changes in climate, economy, technology and culture.



a)

b)

c)

Figure 2. Examples of ludic, hydrological and socio-hydrological time series. a) Fair-sided dice outcomes. b) River Nile at Roda, Egypt: annual minimum levels 622-1284. Note the presence of long-term persistence and memory (Koutsoyiannis, 2013). c) Maya Lowlands: human population history. Note demographic growth periods and collapses, plausibly due to persistent drought conditions (Gill et al., 2007).