

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

Giuliano Di Baldassarre¹, Luigia Brandimarte^{1,2}, Keith Beven^{1,3}

¹*Department of Earth Sciences, Uppsala University, Uppsala, Sweden*

²*UNESCO-IHE Institute for Water Education, Delft, Netherlands*

³*Environment Centre, Lancaster University, Lancaster, United Kingdom*

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

31 reasons not to use uncertainty analysis, while Juston et al. (2013) provided seven reasons to be
32 positive about uncertainty.

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

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

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

54 Aleatory comes from the Latin *alea*, which means a die or game of dice. Aleatory uncertainty
55 is related to the random variability of processes (Koutsoyiannis, 2010; Montanari and
56 Koutsoyiannis, 2012). Probabilistic methods are valuable tools for dealing with the
57 uncertainty related to chance and randomness, which, at the current time, cannot be reduced
58 by improving our knowledge of the systems through scientific efforts. For instance, flood risk
59 is often estimated by referring to the expected annual flood damage (Arnell, 1989) over long
60 time horizons, such as 20 or 30 years. However, the actual damage (direct and indirect,
61 tangible and intangible; see e.g. Giupponi et al., 2014) of future flood events will significantly
62 depend on unpredictable factors, such as the exact time of the day, and day of the week, when
63 the big, extreme flood event will eventually occur (Di Baldassarre et al., 2009a), e.g. the same

64 event would result into significantly different damages if it occurs on Sunday night during
65 summer or during rush hours on a Friday afternoon. While the exact time of occurrence of
66 future flood events cannot be deterministically predicted, this intrinsic uncertainty can be
67 assumed to be predominantly aleatory and can be easily treated in probabilistic terms.

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

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

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

85

86 **Human-water systems**

87 Societies strongly rely on access to water resources, which is essential to support livelihoods
88 and provide favourable conditions for socio-economic development (Di Baldassarre et al.,
89 2010a). While benefiting from water services, humans also alter the hydrological regime
90 (Koutsoyiannis et al., 2009; Vörösmarty et al., 2010; Wagener et al., 2010; Lane et al., 2011).

91 Savenije et al. (2014), for instance, identified four main types of human impacts on
92 hydrology: (i) direct diversion of water flows (water supplies to cities, industries and
93 agriculture), (ii) stream network transformation (construction of dams and reservoirs), (iii)
94 changing river basin characteristics (deforestation, urbanisation, drainage of wet-lands and

95 agricultural practices), and (iv) alteration of the regional or global climate (greenhouse gas
96 emissions and land cover changes).

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

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

105 Recognizing and assessing uncertainty is crucial to provide useful information to decision
106 makers (Pappenberger et al., 2006; Faulkner et al., 2007; Montanari, 2007; Blazkova and
107 Beven, 2009; Koutsoyiannis et al., 2010; Brandimarte and Di Baldassarre, 2012, Beven, 2012;
108 2014; Krueger et al., 2012; Juston et al., 2013). To this end, a number of probabilistic
109 methods have been developed (e.g. Beven, 2009; Di Baldassarre et al., 2010b; Neal et al.,
110 2013). As they are often based on an (unavoidably) incomplete collection of potential
111 scenarios, the issue of what is exactly meant by probability arises. As a matter of fact, the
112 uncertainty affecting the interconnected dynamics of hydrology and society is much more
113 complex than the probabilities that e.g. gamblers estimate when playing dice or enjoying
114 casinos.

115 Figure 2 shows examples of ludic, hydrological and socio-hydrological time series whereby
116 the reliability of probabilistic methods decrease as the seventh facet of uncertainty plays an
117 increasingly major role. The first diagram (Figure 2a) is generated by simulating the outcomes
118 of a fair-sided die, which are assumed independent and identically distributed. This is an
119 example of ludic processes. Ludic comes from the *latin ludus*, which means “play or game”.
120 Taleb (2007) introduced the term “ludic fallacy” to refer to the misuse of the narrow world of
121 games, casinos and dice (whereby probabilities are known) to simulate the uncertainty of real-
122 world processes. The second time series (Figure 2b) is a long time series of hydrological data,
123 i.e. annual minimum water levels of the River Nile at Roda. Figure 2b shows long duration
124 structure, memory and persistence (Koutsoyiannis and Montanari, 2007, Koutsoyiannis,
125 2013). Probabilistic methods can still be used to handle this type of uncertainty, but they
126 require the identification of a model of the underlying stochastic structure (Montanari and
127 Koutsoyiannis, 2012). Lastly, the third time series (Figure 2c) refers to the growth and

128 collapse of the Maya civilization. It shows the evolution of the human population over
129 centuries and the potential relations with hydrological conditions. It has been showed, for
130 instance, how technological revolutions triggered population and economic growth in the
131 Maya lowlands, whereas the persistence of drought conditions eventually led to the societal
132 collapse (Haug et al., 2003; Gill et al., 2007). However, it is difficult to rigorously test these
133 causal links because the temporal resolution of human population data reconstructed from
134 archeological records is very coarse (Figure 2b), while the proxies used for dating historical
135 droughts are affected by significant uncertainties (Aimers and Hodell, 2011; see also
136 Yancheva, 2007 and related discussion).

137

138 **Known unknowns**

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

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

152 The levée paradox is an example of a known unknown. The paradox was already identified by
153 White (1945) and has been discussed by several authors (Kates et al., 2006; Montz and Tobin,
154 2008; Di Baldassarre et al., 2009b; Castellarin et al., 2011; Viglione et al., 2014). Most flood
155 scientists know about it. Yet, methods to capture it in the assessment of future flood risk
156 (which can be defined as a combination of flooding probability and potential adverse
157 consequences) are completely lacking. For instance, when flood defense structures are
158 planned and designed, current methods can indeed estimate the corresponding reduction of

159 flooding probability. However, they do not assess how such a reduction might trigger an
160 increase of the adverse consequences of flooding.

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

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

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

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

188 Historical analyses of human-water interactions over long time scales, i.e. centuries, can be
189 very challenging. The aforementioned example of the collapse of the Maya civilization shows
190 the issues encountered when dealing with long time series of archeological data (human

191 population, Figure 2c) and proxies of historical climate conditions: causality links between
192 social and hydrological dynamics are difficult to test (Yancheva, 2007; Aimers and Hodell,
193 2011). Nevertheless, empirical studies of human-water interactions at time scales relevant for
194 water management and disaster risk reduction, i.e. years to decades, can be much more
195 feasible. Urbanized deltas and floodplains, for instance, are examples of ideal laboratories for
196 the (inter- or trans-disciplinary) study of the interplay between social and hydrological
197 processes as the interactions between human and water systems are apparent and have
198 relevant impacts (Di Baldassarre et al., 2013a). In these flood-prone areas, human settlements,
199 flood control measures, and memory of flooding have gradually co-evolved at similar
200 temporal (years to decades) and spatial (floodplain) scales, while they have been also
201 significantly affected by the sudden and localized occurrence of flooding events.

202 Long time series of demographic, economic and hydrological data along with information
203 about human adjustments to floods are already available for many case studies, such as New
204 Orleans, the Tiber in Rome, and the Dutch delta (Werner and McNamara, 2007; Aldrete,
205 2007; de Moel et al., 2011). Yet, to understand the dynamics emerging from the poorly
206 explored interactions and feedbacks between human and water systems, there is a need to start
207 collecting more empirical evidence. Socio-hydrological models (Di Baldassarre et al., 2013b,
208 Viglione et al., 2014) can provide insights about the type of data that we need to collect to
209 observe the dynamic interplay between physical and social processes. Hence, we think that
210 more observations and empirical studies can significantly contribute to a better understanding
211 of the dynamics of human-water systems and therefore reduce this type of epistemic
212 uncertainty.

213

214 **Unknown unknowns**

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

223 contingencies. However, after they occur, humans tend to over-react and over-estimate their
224 probability, potentially leading to some unintended consequences.

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

240 Thus, potential surprises and black swans suggest the need to go beyond heavy reliance on
241 predictions, and traditional top-down approaches based on probabilistic assessments of
242 hydrological hazards. In this context, Blöschl et al. (2013) comprehensively discussed the
243 potentialities of complementing traditional top-down approaches with bottom-up ones.
244 Bottom-up approaches do not start from probabilistic prediction, but, rather, from the societal
245 and economical vulnerability of communities and individuals and explore the possibilities
246 (rather than the probabilities) of failures by explicitly considering the expertise of local
247 stakeholders and risk managers (see e.g. Lane et al., 2011). For instance, Wilby and Dessai
248 (2010) showed how the vulnerability of the human-water systems to droughts and water
249 scarcity can be reduced by enhancing the connectivity of water supply infrastructures and
250 making abstraction licenses time-limited. While this combination of measures could not be
251 considered "optimal", it is more robust than alternative low-regret options to the potential
252 occurrence of unexpected events with potentially devastating consequences. Thus, it is by
253 acting from a vulnerability's viewpoint that water managers and scientists can reduce the
254 negative impacts of unknown unknowns and potential surprises.

255

256 **Wrong assumptions**

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

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

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

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

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

274 The point made by Smart Angie is that the coin must be loaded. In classical terms, odds of the
275 coin coming up heads 99 times in a row are so low that the *assumption* that the coin had a
276 50% chance of coming up heads *is most likely wrong*.

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

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

293 When it comes to the non-linear dynamics of human-water systems, the issue of making
294 fundamentally wrong assumptions becomes even larger as the perception of hydrological
295 change and attitude towards risk can strongly vary across human societies depending on
296 political and socio-economic conditions as well as cultural values (Kahneman and Tversky,
297 1979; Thompson et al., 1990; Viglione et al., 2014). And given wrong assumptions, of course,
298 we should expect surprises in the future (as seen also in other disciplines, such as economics).

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

306

307 **Conclusions**

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

315 The increasing impact of human activities on hydrological dynamics, in a time that some calls
316 Anthropocene, has led to a growing interest on the study of water-society interactions. As the
317 dynamics of human-water systems are still largely unknown, and social dynamics are highly

318 unpredictable, we argued that there is a need to go beyond current approaches (focusing on
319 uncertainty as randomness and probabilistic methods) and give more credit to the seventh
320 facet of uncertainty. In particular, we proposed new observations and empirical studies of
321 coupled dynamics of hydrology and societies to increase our knowledge of the behaviour of
322 fully coupled human-water systems and reduce epistemic uncertainty. Hence, scientific
323 understanding is believed to be a way to deal with wrong assumptions and known unknowns
324 in the study of the interplay between social and hydrological processes, which one of the main
325 focuses of Panta Rhei, the current IAHS's scientific decade.

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

330

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336

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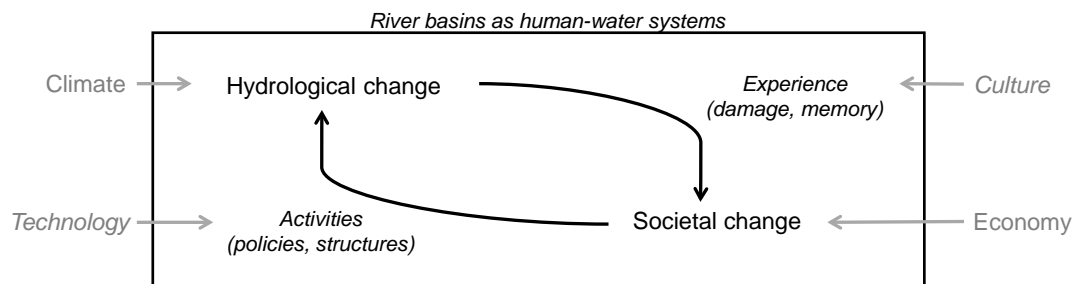
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502 **Figures**

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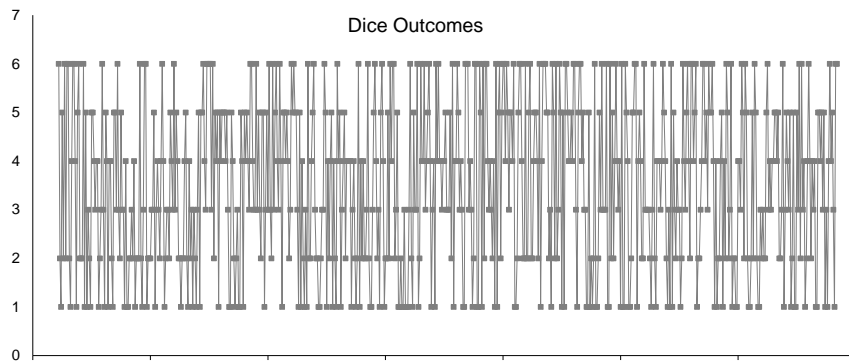
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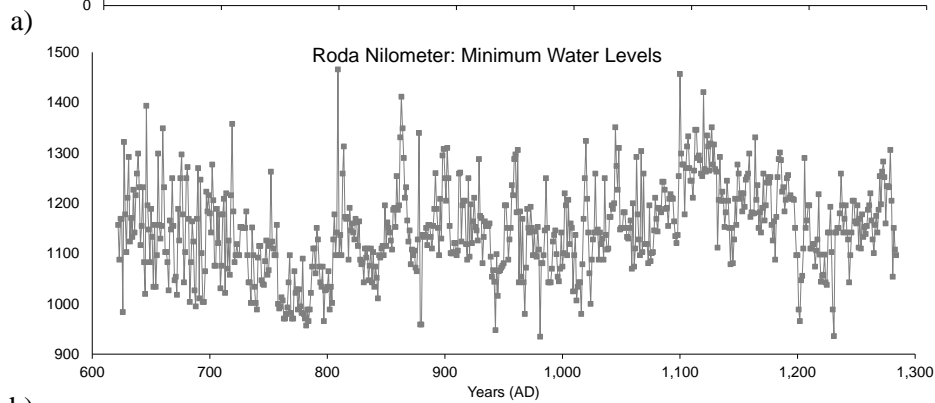
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506 **Figure 1.** The socio-hydrological cycle: societies change the hydrological regime via human activities,
507 while the experience of hydrological changes shape societies. Human and water systems are deeply
508 intertwined and respond to global changes in climate, economy, technology and culture.
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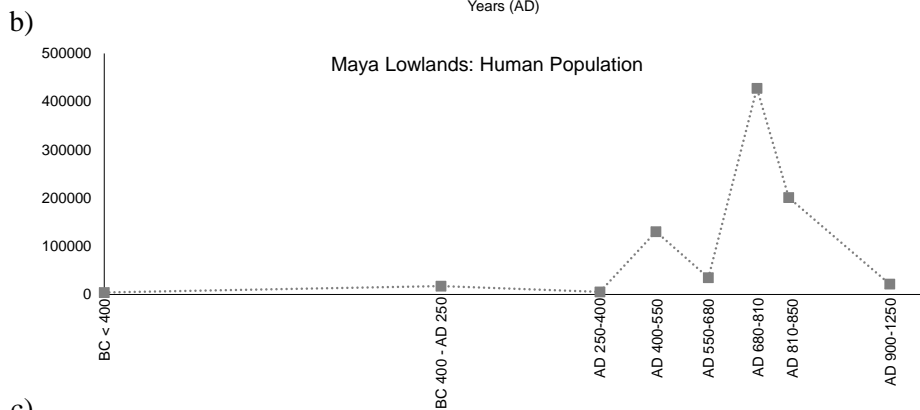
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516 **Figure 2.** Examples of ludic, hydrological and socio-hydrological time series. a) Fair-sided dice
517 outcomes. b) River Nile at Roda, Egypt: annual minimum levels 622-1284. Note the presence of long-
518 term persistence and memory (Koutsoyiannis, 2013). c) Maya Lowlands: human population history.
519 Note demographic growth periods and collapses, plausibly due to persistent drought conditions (Gill et
520 al., 2007).
521