

1                   **Modeling and Mitigating Natural Hazards: Stationarity is Immortal!**

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7  
8           **Abstract**

9           Environmental change is a reason of relevant concern as it is occurring at an unprecedented  
10           pace and might increase natural hazards. Moreover, it is deemed to imply a reduced  
11           representativity of past experience and data on extreme hydroclimatic events. The latter  
12           concern has been epitomized by the statement that “stationarity is dead”. Setting up policies  
13           for mitigating natural hazards, including those triggered by floods and droughts, is an urgent  
14           priority in many countries, which implies practical activities of management, engineering  
15           design and construction. These latter necessarily need to be properly informed and therefore  
16           the research question on the value of past data is extremely important. We herein argue that  
17           there are mechanisms in hydrological systems that are time invariant, which may need to be  
18           interpreted through data inference. In particular, hydrological predictions are based on  
19           assumptions which should include stationarity, as any hydrological model, including  
20           deterministic and non-stationary approaches, is affected by uncertainty and therefore should  
21           include a random component that is stationary. Given that an unnecessary resort to non-  
22           stationarity may imply a reduction of predictive capabilities, a pragmatic approach, based on  
23           the exploitation of past experience and data is a necessary prerequisite for setting up  
24           mitigation policies for environmental risk.

27 **Introduction**

28 Facing environmental risk has always been a challenge for societies and is a matter of  
29 growing concern today. On the one hand, the increased impacts of extreme events, along with  
30 the observation that the environment is changing at an unprecedented pace, highlight that  
31 human settlements are more and more exposed to natural hazard and risk. On the other hand,  
32 the explanation and attribution of the above increased risk are open research questions in  
33 hydrology, and social sciences as well. Consequently, calls are being issued for an improved  
34 understanding and interpretation of environmental change [*Montanari et al.*, 2013] and its  
35 connection with society, through the study of the two-way interaction between environment  
36 and humans [*Sivapalan et al.*, 2012; *Di Baldassarre et al.*, 2013; *Ceola et al.*, 2014;  
37 *Koutsoyiannis*, 2013; *Viglione et al.*, 2014; *Montanari et al.*, 2014; *Sivapalan et al.*, 2014].  
38 The awareness of the importance of the research themes related to change, in connection with  
39 evolving societal systems, recently led the International Association of Hydrological Sciences  
40 (IAHS) to focus on these topics during the Scientific Decade 2013-2022, by launching the  
41 Panta Rhei research initiative [*Montanari et al.*, 2013; *Montanari et al.*, 2014;  
42 [www.iahs.info/pantarhei](http://www.iahs.info/pantarhei)].

43 Given the urgency of environmental change and environmental risk, a pragmatic and holistic  
44 approach is needed to immediately focus on the above research questions. We believe that  
45 research activities should identify effective and technically sound solutions, by clarifying to  
46 what extent and why the environment is changing and how design variables should be  
47 estimated under change. To this end, we need to investigate what useful information is already  
48 available, what further information is necessary and what approaches should be considered.  
49 Many of the fatalities that occur each year during extreme events could be avoided by setting  
50 up simple precautionary actions, yet these are frequently not identified a priori. Research  
51 activity is urgently needed to identify critical locations and priorities for mitigation.

52 A key premise to reach the above goals is to clarify how to best profit from experience, data

53 and information in the face of a rapidly changing environment. There is a widespread  
54 perception that the past is no more representative of the future. These beliefs have been  
55 epitomized by the statement “stationarity is dead” [Milly *et al.*, 2008] which has been lately  
56 very popular in the hydrological community, while few have criticized it [Koutsoyiannis,  
57 2011; Lins and Cohn, 2011; Matalas, 2012; Koutsoyiannis and Montanari, 2014]. The  
58 conviction that stationarity is dead led to claims that paradigm shifts should be pursued in  
59 hydrology to elaborate new philosophies and methods [Milly *et al.*, 2008]. The shift would be  
60 towards methods that are driven by deterministic models and future forcing scenarios that  
61 would replace the assumption of stationarity. These would be elaborated upon an improved  
62 understanding and modeling of the underlying processes. We believe that this is not  
63 necessarily the most efficient way to draw predictions and therefore we aim to discuss the  
64 above premise in the context of hydrological modeling and engineering design in a changing  
65 environment. We elaborate on this issue here below, by focusing on the specific case of  
66 environmental risks related to water and hydrology.

67

### 68 **Defining the problem**

69 The practical problem is simple to state: how to efficiently identify and plan mitigation  
70 policies for natural disasters caused by hydroclimatic extremes, through environmental  
71 planning and engineering design. Engineers traditionally tackled this challenge by observing  
72 the phenomena, making predictions (mostly of statistical type) on likely future occurrences  
73 and finally designing mitigation actions. Examples of these latter are catchment management,  
74 construction of flood retention reservoirs, river engineering works and non-structural  
75 measures [Thampapillai and Musgrave, 1985; Kundzewicz, 2002]. Engineers were always  
76 aware of uncertainty, which may also be amplified by environmental changes, and therefore  
77 developed appropriate methodologies to quantify it and used safety factors in the design  
78 process [Beven, 2013].

79 Today, instances of failure of mitigation policies and protecting structures that were set up a  
80 long time ago are often interpreted as a sign that the traditional design methods are inefficient  
81 to face current risks. Therefore, new modeling approaches are invoked [*Schaepli et al.*, 2011].  
82 Are they really necessary? Or is the pursuit of new approaches just a manifestation of  
83 departure from scientific and engineering thinking, combined with the radical reduction of  
84 investment in engineering infrastructure [*Koutsoyiannis*, 2014]?

85

### 86 **Approaches for environmental modeling**

87 Models are essential to better understand hydrological systems and to design mitigation  
88 actions for hydrological risk. Design is always carried out by using models, sometimes  
89 implicitly. For instance, the estimation of the peak river flow for an assigned return period is  
90 carried out by using models of various types. Identifying the appropriate model is a crucial  
91 step in engineering design [*Laio et al.*, 2009].

92 A multitude of approaches have been proposed for environmental modeling. Such models  
93 typically refer to the transformation of inputs of a system to outputs. They can be broadly  
94 divided in two classes (see Figure 1): deterministic and non-deterministic (statistical or  
95 stochastic) models. We believe it is important to clarify the advantages and drawbacks of such  
96 categories when dealing with change.

97 In a deterministic formulation the system output is uniquely determined by the input. Namely,  
98 input data are precisely associated to the model response and therefore uncertainty in the  
99 model structure is not directly taken into account. The popularity of deterministic approaches  
100 leading to deterministic predictions has considerably been increased in recent times. Two  
101 factors may have contributed to such popularity. First, the ever increasing power of  
102 computers, which can provide, in reasonable time, numerical solutions of dynamical systems  
103 (typically described by differential or difference equations), led many to develop the belief  
104 that natural systems can be modeled fully deterministically and with precision, once a

105 sufficient level of detail (reflected in spatio-temporal resolution) is achieved in system  
106 description [*Koutsoyiannis et al., 2009*]. Second, the culture developed within climate change  
107 exploration and spread in many disciplines including hydrology, led many to deem future  
108 scenarios obtained with deterministic models as credible predictions of the distant future.

109 The argument behind such reasoning is that assuming (a) perfect knowledge of the considered  
110 hydrological system, which enables a complete and precise description, (b) perfect knowledge  
111 of initial and boundary conditions, (c) perfect information to identify precise model  
112 parameters and feed a model with input data, then a deterministic model of the system would  
113 allow to make perfect predictions of the outputs for whatever lead time (up to centuries), thus  
114 providing an ideal solution to any type of problem. With such a model, change would not be a  
115 matter of concern anymore, as in a perfectly described system any shifting regime could be  
116 precisely modeled and predicted. Indeed, deterministic models allow one to account for  
117 causality with mechanistic solutions and therefore provide a valuable opportunity. However,  
118 we note that deterministic hydrological models need to be calibrated and therefore their use  
119 will never eliminate the need to make statistical inference from historical information. More  
120 importantly, one should note that in hydrology deterministic predictions are inevitably  
121 affected by several uncertainties due to imperfect geometric description of the control volume,  
122 inexact initial and boundary conditions [*Koutsoyiannis, 2010*], limited and often erroneous  
123 observability of the hydrological and meteorological variables [*Beven and Westerberg, 2011*;  
124 *Di Baldassare and Montanari, 2009*; *Montanari and Di Baldassarre, 2012*], imperfect model  
125 structure [*Beven, 2012*; *Gupta et al., 2012*], imperfect parameters and, as far as the future is  
126 concerned, unknown inputs. In such a situation, predictions can still be elaborated and can  
127 still be useful, but randomness and uncertainty need to be taken into account [*Vogel, 1999*].

128 The presence of randomness is the reason why engineering hydrology frequently relied on  
129 non-deterministic models and in particular statistical approaches. The use of statistics was  
130 induced by understanding, rather than ignorance, of the underlying processes [*Yevjevich,*

131 1974]. For instance, when the considered phenomena is described by a model with a high  
132 degree of non-linearity, a deterministic prediction is not possible even when the system is  
133 fully understood, while a stochastic prediction may allow one to draw probability  
134 distributions of future occurrences. In fact, for any perfect deterministic system, including  
135 linear models with some uncertain components, statistical predictions are the only viable ones  
136 for long time horizons [*Koutsoyiannis, 2010*]. In view of the above reasoning we conclude  
137 that using a stochastic approach, with a physical basis, is needed in hydrology.

138 No matter what approach is used, the modeling strategy to obtain design variables is based on  
139 the identification of invariant properties of the investigated phenomena to devise the model  
140 structure and inform the prediction. In the case of deterministic modeling these invariant  
141 properties may be, for instance, quantities like mass, momentum, angular momentum, energy  
142 and others [*Koutsoyiannis, 2011*]. In stochastic modeling of complex systems the preservation  
143 of only these invariant quantities does not suffice as a model basis and therefore some  
144 statistical properties of the studied stochastic process are computed by using past data and are  
145 assumed to be time invariant, provided that such assumptions are consistent with the data and  
146 the process understanding. The assumption that the above statistics are time invariant is called  
147 “stationarity” [*Kolmogorov, 1931; Khintchine, 1934; see also Koutsoyiannis and Montanari,*  
148 2014].

149 Now, an important question today is: should a physically-based stochastic approach rely on  
150 the hypothesis of stationarity, even in the presence of change? Would this assumption be still  
151 reliable and useful? And, if not, what alternative assumption should one use? Is non-  
152 stationarity a useful way forward to deal with technical problems? Is the past still  
153 representative of the future? Can historical data inform engineering design and mitigation  
154 policies for natural hazards?

155

156 **Stationarity**

157 To address the above research questions, it is necessary to clarify the meaning and technical  
158 implications of stationarity and the meaning of the related statement that the past is  
159 representative of the future (or not).

160

### 161 *Theory of Stationarity*

162 We mentioned above that stationarity is an assumption introduced when making inference and  
163 prediction. In rigorous terms and according to the original definition [*Khintchine*, 1934;  
164 *Kolmogorov*, 1938], a stochastic process  $X(t)$  is stationary if and only if

$$165 \quad F(x_{t_1}, x_{t_2}, \dots, x_{t_n}) = F(x_{t_1+\tau}, x_{t_2+\tau}, \dots, x_{t_n+\tau}), \forall n, t_1, t_2, \dots, t_n, \tau \quad (1)$$

166 where  $F(\cdot)$  denotes the joint probability distribution function. Given that  $F(\cdot)$  does not change  
167 with a time shift  $\tau$ , it follows that the statistics of a stationary stochastic process do not change  
168 in time (for more details see *Kolmogorov* [1931, 1938], *Khintchine* [1934] and *Koutsoyiannis*  
169 *and Montanari* [2014]). It is important to note that the definition implies that the process is  
170 stochastic and does not imply that the state of the process itself does not change. Actually, a  
171 stationary process, as was introduced in the works of Kolmogorov and Khintchine, undergoes  
172 change, but its statistics are conserved in time. Therefore, change does not imply non-  
173 stationarity and stationarity does not imply at all unchanging process state.

174 In view of the above definition, one can conclude that non-stationarity necessarily implies that  
175 some of the process statistics are time varying.

176

### 177 *Stationarity and non-stationary models*

178 When interpreting with mathematical models environmental processes non-stationarity may  
179 be justified and therefore a non-stationary model may be applied. However, this will never be  
180 perfect and therefore it will lead to residuals that will necessarily be treated as stationary if a  
181 good fit of change is obtained. Therefore, the use of a non-stationary model does not allow  
182 one to get rid of stationarity: namely, the modeling of change, in any case, must be based on

183 the identification of invariant statistical properties and observed data are the necessary means  
184 to attain this goal.

185 A first implication of the use of a non-stationary model is that additional parameters are  
186 needed. If non-stationarity is properly described, the non-stationary model will lead to less  
187 biased simulation of future conditions, but the variance of the estimates will increase, for the  
188 above mentioned increased number of parameters. Therefore, one should evaluate whether the  
189 reduction of bias is worth the increased variance. Indeed, the selection of a non-stationary  
190 rather than stationary approach should be framed as a standard model selection problem  
191 where one selects the best model, namely, the one that produces the best design variables in  
192 terms of bias and variance of the estimates. Better estimates imply a more successful design  
193 not only in terms of reliability and durability of the proposed solutions, but also in terms of  
194 their cost effectiveness and therefore economical feasibility. The above mentioned increased  
195 variance of the estimates provided by a non-stationary model, due to a larger number of  
196 parameters, may imply an increase of the economic costs of the proposed solutions, therefore  
197 reducing their feasibility. Non-stationarity is just an option and not a universal solution to  
198 modelling environmental change. We maintain that engineers and technicians need to adopt  
199 the most reliable approach in view of the available information.

200 A second implication of the use of a non-stationary model is that its statistics necessarily are a  
201 deterministic function of time [*Koutsoyiannis*, 2011; *Koutsoyiannis and Montanari*, 2014].  
202 The term “deterministic” is extremely important here, as it underlines that the use of a non-  
203 stationary approach, particularly in engineering design, must be based on the identification of  
204 a deterministic relationship identified by logics, mathematics or physics and also verified by  
205 the data, to explain the change in time of some statistics of the process (see Figure 1). In  
206 absence of such deterministic attribution, one cannot introduce any assumption of non-  
207 stationarity and therefore a non-stationary model cannot be set up. We realize that this latter  
208 statement is crucial for delivering our message efficiently and therefore would like to clarify it

209 further.

210 In fact, our assertion above may be questioned by one who is convinced that a process is non-  
211 stationary because its statistics may change in time according to a random process. However,  
212 this is not possible, as process statistics are deterministic variables (typically unknown  
213 constants) by definition and the model would be ill-defined or even meaningless if they were  
214 assumed to be random. For instance, take the mean value of a generic, real-valued, random  
215 variable which is defined as

$$216 \quad E[X(t)] = \int_a^b xp(x;t)dx \quad (2)$$

217 where  $p(x;t)$  is the probability density of the outcome  $x(t)$  from the random variable  $X(t)$  at  
218 time  $t$  and  $[a, b]$  is the interval of real values over which  $X$  is defined. Given that a stochastic  
219 process is a collection of random variables, each representing all possible values of the  
220 process at a given time step, the process itself will be characterized by an assigned mean value  
221 at each time  $t$ . According to eq. (1), the mean of the process  $E[X(t)]$  will be given as a  
222 deterministic function of time, taking identical values if the process is stationary ( $E[X(t)] =$   
223  $E[X]$ ). The case in which statistics may randomly vary is therefore excluded. Let us provide  
224 an example, by referring to a Gaussian white noise  $X(t)$  with mean  $\mu_X$  and standard deviation  
225  $\sigma_X$ . Now, let us assume that  $\mu_X$  is replaced by another Gaussian white noise  $Z(t)$  with mean  $\mu_Z$   
226 and standard deviation  $\sigma_Z$ , therefore assuming that the mean of  $X(t)$  is random. Then, another  
227 Gaussian process  $Y(t)$  is obtained, with  $\mu_Y = \mu_Z$  and standard deviation  $\sigma_Y = (\sigma_X^2 + \sigma_Z^2)^{0.5}$ .  
228 Therefore, the statistics of  $Y(t)$  are deterministic constants and not random variables and thus  
229  $Y(t)$  is stationary.

230 One may say that prior information may allow one to know that the statistics of the process  
231 are changing (and/or will change) and therefore the process is non-stationary, but the shape of  
232 the change may still be unknown; therefore the process is non-stationary even though one is  
233 not allowed to assume any deterministic relationship explaining the progress of statistics in  
234 time. Such statement would also be incorrect. In fact, the above situation would imply that

235 one is not allowed to set up any non-stationary model to explain an evolution that is unknown  
236 and therefore the use of the concept of non-stationarity is not possible. Changes in the  
237 statistics of the process which are unpredictable (or unknown) result in a stationary approach  
238 – not a non-stationary one.

239 The above need for a deterministic relationship to explain the progress in time of the process  
240 statistics, in order to claim non-stationarity, is extremely important because it emphasizes that  
241 a proper justification is needed for using a non-stationary model in technical applications.  
242 There are indeed cases where the use of a non-stationary description is justified. If we knew  
243 the evolution in time of hydrological characteristics and parameters (in addition to  
244 hydrological observations, we may have information about how the percent of urban area  
245 changed in time, for instance), then we can build a non-stationary model, where the available  
246 information allows one to reduce the bias of the predictions. One should note that, even in the  
247 latter case, the non-stationary model will anyway include a random component that is  
248 stationary. In contrast, if we see a changing behaviour but we do not have any quantitative  
249 information, then particular care should be used if we decide to set up a non-stationary model  
250 that would be based on information that may be unreliable. For instance, it is frequent practice  
251 in environmental modeling to estimate the above deterministic changes of the process  
252 statistics by using “projections” of future environmental and climatic conditions that are  
253 obtained by applying models (for instance climatic models; see *Milly et al.* [2008]).  
254 Reliability of these projections is a necessary condition for obtaining less biased estimates,  
255 and therefore better defined mitigation policies for environmental risks. If projections are not  
256 reliable, not only the variance of the estimates will increase; their bias will increase as well  
257 and therefore non-stationary models may turn out to be less efficient with respect to their  
258 stationary counterpart. In order to properly inform model selection, the uncertainty of the  
259 above projections needs to be carefully evaluated. If projections are highly uncertain, a  
260 stationary model may well turn out to be the best solution for technical problem solving.

261 While non-stationarity necessarily needs to be described by a deterministic change of process  
262 statistics, it is important to emphasize that the introduction of a deterministic component in a  
263 stochastic process, to take into account the knowledge of the underlying phenomenon, does  
264 not necessarily imply that the resulting random process is non-stationary. For instance,  
265 accounting for seasonality through a deterministic description leads to a cyclostationary  
266 process, which in aggregate scales is stationary.

267

### 268 *Implications of stationarity in engineering design*

269 The above discussion brings to the following conclusions that we believe are extremely  
270 important in engineering design. (1) Stationarity is a concept that applies to stochastic  
271 processes and the assumption of non-stationarity needs to be supported by a deterministic  
272 description of the process statistics along time (Figure 1). (2) Any deterministic change of the  
273 process statistics is superimposed on a random component (unexplained variability) that is  
274 necessarily stationary. Namely, any random process – no matter if stationary or not –  
275 necessarily includes a stationary component, and therefore any future prediction needs to  
276 ultimately rely on the assumption of stationarity of that random part. (3) If a deterministic  
277 description of the process statistics along time, applicable to future times, is not available,  
278 which implies that non-stationarity is impossible to define, the only way for making  
279 predictions is through the assumption of stationarity. (4) The selection of a non-stationary  
280 model, rather than a stationary one, must be supported by a proper model selection analysis,  
281 as non-stationary models may turn out to be a less efficient solution in view of their increased  
282 uncertainty. A reduced robustness of the design variables is certainly something that engineers  
283 want to avoid when dealing with natural hazards. The latter considerations justify why  
284 engineers often rely on the assumption of stationarity.

285 Therefore we can conclude that stationarity is still a necessary concept in engineering design.

286 Unfortunately, several different meanings are attributed to the term “stationarity” in modern

287 hydrology (as explained by *Koutsoyiannis* [2011] and *Thompson et al.* [2013]). We believe  
288 that redefining concepts that are largely used in practice brings the risk to induce  
289 misconceptions. In the specific case of environmental risk mitigation, claiming that  
290 stationarity should be abandoned would imply that mitigation policies are not properly  
291 identified. Therefore, we believe it is appropriate to refer to the original definition of  
292 stationarity as proposed by *Kolmogorov* [1931,1938] and *Khintchine* [1934].

293

### 294 **Dealing with change**

295 The above summary of the situation clarifies how hydrological change can be defined and  
296 quantified [see also *Ceola et al.*, 2014]. If one sticks to a deterministic representation, change  
297 is defined through the study of the process behavior. If a physically-based stochastic  
298 representation is used, which we believe is the appropriate solution, two ways forward can be  
299 identified: (1) if the natural process is modelled as stationary, change is quantified by relying  
300 on the hypothesis of stationarity, studying past patterns, gaining a knowledge of the process  
301 allowing to include the known physical basis, and making statistical inference and  
302 predictions; (2) if non-stationarity is justified, change is dealt with in the same way as for  
303 stationary processes but deterministic relationships are introduced for its statistical properties  
304 instead of assuming them constant, by investigating past patterns and exploiting information  
305 for the future, provided that such information is deemed reliable. In any case, the analysis of  
306 the past, through data, is an essential step to elaborate predictions, together with the analysis  
307 of any other hydrological information and assessment of the applicability of deterministic  
308 relationships for the future statistics.

309

### 310 **Is environmental change non-stationary? Is stationarity dead?**

311 The above considerations make clear that environmental change can be (in our opinion should  
312 be) modeled as a physically-based stochastic process, which in general can be stationary and

313 only in justified cases non-stationary, and observations and information are key elements for a  
314 successful prediction. In fact, in view of the considerations that we developed so far in this  
315 paper, we are convinced that the question of whether change should be modeled within a  
316 stationary or non-stationary setting should be viewed in the frame of its relevance in solving  
317 practical problems. Of course modeling solutions depend on the nature of the process, but  
318 stationarity and non-stationarity are just two different options for building a physically-based  
319 stochastic model. In model building it is quite important to identify behaviors and parameters  
320 by analyzing past patterns using evidence provided by observations. But most important of all  
321 is to provide reliable and effective solutions to the real world problems; otherwise the debate  
322 about stationarity becomes a discussion on just semantics. In the case of mitigation of natural  
323 hazards, solving practical problems implies the design of management policies and  
324 engineering structures that need to be based on the estimation of design variables and their  
325 uncertainty, which is strictly related to economical feasibility of solutions.

326 After the above discourse, we have no doubt to conclude that stationarity cannot be dead: it is  
327 a modeling convenience that allows one to make reliable predictions for engineering design  
328 rather than a real world entity. Modeling concepts will only die if they are useless. We are  
329 convinced that the stationarity concept is quite useful because it highlights the fact that,  
330 whatever deterministic controls and mechanisms are identified and whatever progress is made  
331 in deterministic modeling, there will always be unexplainable variability in any system for  
332 which a probabilistic description assuming stationarity is needed. We believe that both exact  
333 predictability (particularly for distant times) and inference without data are impossible while  
334 only (physically-based) stochastic modeling offers a pragmatic solution. In this respect, it is  
335 not paradoxical to conclude that stationarity is immortal, as immortal is the need for statistical  
336 descriptions and the need to seek robust solutions to practical problems.

337

338 **Concluding remarks**

339 To conclude with some practical considerations, we first emphasize once again the importance  
340 of data. Data, and therefore the observation of the past, are the key to reach a better  
341 understanding of change, to improve our knowledge of hydrological processes and to make  
342 predictions for the future. The information available to hydrologists is tremendously  
343 increasing and therefore a concerted effort is needed by the hydrologic community to: (a)  
344 propose initiatives to support data accessibility and data sharing, (b) formulate advanced  
345 methods for integrating several sources of different information, (c) identify critical data gaps  
346 and (d) advance monitoring means. These should be high priorities for researchers working on  
347 hydrological change and environmental risk.

348 Second, we are convinced that a perfect deterministic description of hydrological systems will  
349 never be possible [*Koutsoyiannis, 2010; Montanari and Koutsoyiannis, 2012; Montanari and*  
350 *Koutsoyiannis, 2014; Ceola et al., 2014*] and therefore a physically-based stochastic  
351 description, based on the analysis of past patterns (and possibly non-stationary but always  
352 allowing a transformation that would lead to stationarity, i.e. invariance in time of statistical  
353 properties of some transformation of the process of interest), is the way forward to gain an  
354 improved understanding and seek efficient solutions to deal with environmental risk. This is  
355 also the concept and the approach that is used in other disciplines like seismology and  
356 volcanology [*Vere-Jones et al., 2005; Mader et al., 2006*].

357 In discussions about stationarity or non-stationarity we should bear in mind that this is a  
358 research question, which has practical consequences with respect to the use of available  
359 information in the design of structures and management policies. For the latter, a holistic and  
360 practical approach should be adopted. There is no need to rethink hydrology from scratch, nor  
361 to promote paradigm shifts or to build new sciences: practical problems solving should be  
362 based on finding the best way to profit from experience, to profit from new information and  
363 computational means. For the purpose of deepening our knowledge of hydrological processes,  
364 it is necessary to recognize their random character while improving prediction models. We

365 propose to look at the future with an optimistic perspective of the opportunities that  
366 randomness offers. We do not need to seek an impossible determinism to cope with natural  
367 hazards: we just need forward looking and pragmatic ideas to profit from ever improving  
368 knowledge and information.

369

### 370 **Post scriptum – Statistics versus process understanding**

371 We believe that there is a widespread misconception in the hydrologic community, related to  
372 the use of process-based versus statistical models. The prevailing view is that process-based  
373 deterministic models are deductive means that take advantage of the available knowledge of  
374 the process dynamics, while statistical models are inductive and therefore are useful when the  
375 above knowledge is limited. We believe that this view is inconsistent. In complex  
376 hydrological systems, both deterministic and stochastic models are necessarily inductive (as  
377 they rely on fitting on data), while any deductive component in a deterministic model can be  
378 conveyed also in a stochastic model [*Montanari and Koutsoyiannis, 2012*]. The actual  
379 difference between deterministic and statistical models is just that the former establish a  
380 precise relationship between input (including initial and boundary conditions) and output  
381 (including systems state), while the latter examines the probabilities of events (or time  
382 evolution thereof) by admitting that randomness, and therefore uncertainty, is inescapable. A  
383 statistical or stochastic model is just not deterministic: it can be physically-based, it can  
384 represent spatial and time variability and can take full advantage of the knowledge of the  
385 system. Because of this, stochastic models with an increasing content of physical reasoning  
386 have been gaining increasing attention over the last decades. In order to identify the  
387 appropriate model to use, one should simply decide whether one wants to represent the  
388 inherent randomness affecting hydrological processes, and whether or not one wants to take  
389 uncertainty into account. There is no doubt that process-based models are the most  
390 appropriate solution for solving many water related problems, but we do not see any reason

391 not to formulate them in a stochastic context. In our opinion, stochastic-process-based models  
392 are the way forward to bridge the gap between physically-based models without statistics and  
393 statistical models without physics. There has been a lot of applications in hydrology that  
394 clarified the potential of stochastic process-based models (see, for instance, *Montanari and*  
395 *Koutsoyiannis* (2012); *Langousis et al.* (2008); *Langousis and Veneziano* (2009a; 2009b)).

396

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521 **FIGURE CAPTIONS**

522

Model type	Studied properties	Stationary case	Nonstationary case
<b>Deterministic</b>	Evolution in time of system states without reference to statistical properties	Not applicable	Not applicable
<b>Non-deterministic (statistical/stochastic)</b>	Evolution in time of probabilities of systems states or statistical properties thereof	Probabilities and statistical properties are assumed constant in time	Probabilities and statistical properties are changing according to deterministic functions of time

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Figure 1. Classification of modeling approaches, studied properties and behaviors in the stationary and non-stationary case.