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1 **ASSESSING BASEFLOW INDEX VULNERABILITY TO VARIATION IN DRY SPELL**  
2 **LENGTH FOR A RANGE OF CATCHMENT AND CLIMATE PROPERTIES**

3

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11 **Abstract**

12 Baseflow index (BFI) prediction in ungauged basins has largely been based on the use of catchment  
13 physiographic attributes as dominant variables. In a context where changes in climate are  
14 increasingly evident, it is also important to study how the slow component of flow is potentially  
15 affected by climate. The aim of this study was to illustrate the impact of climate variability on the  
16 baseflow process based on analysis of daily rainfall characteristics and hydrological modelling  
17 simulation exercises validated with observed data. Ten catchments were analysed that span southern  
18 to northern Europe and range from arid Mediterranean to maritime temperate climate conditions.  
19 Additionally, more than two thousand virtual catchments were modelled that cover an extended  
20 gradient of physiographic and climate properties. The relative amounts of baseflow were  
21 summarized by the BFI. The catchment slow response delay time ( $K_s$ ) was assumed to be a  
22 measure of catchment effects, and the impact of climate properties was investigated with the dry  
23 spell length ( $d$ ). Well-drained and poorly-drained groups were identified based on  $K_s$  and  $d$ , and  
24 their response to an increase or decrease in dry spell length was analysed. Overall, for either well-  
25 or poorly-drained groups, an extension in dry spell length appeared to have minor effects on the  
26 baseflow compared with a decrease in dry spell length. Under the same dry spell variation, the BFI  
27 vulnerability appeared higher for catchments characterized by large initial  $d$  values in combination  
28 with poorly-drained systems, but attributing an equal weight to the variations in  $d$  both in the case  
29 of dry and wet initial conditions, it is in the end concluded that the BFI vulnerability appear higher  
30 for systems laying in the transition zone between well- and poorly-drained systems.

31

32 **Keywords:** Baseflow, Low flows, BFI, Dry spells, IAHCRES, catchment characteristics, climate

33

## 34 1. INTRODUCTION

35 The baseflow index (BFI), the ratio between the volume of baseflow and the volume of total  
36 streamflow, was originally recommended in the Low Flow Studies ([Institute of Hydrology, 1980](#))  
37 for indexing the effect of geology on low flows; however, the BFI now represents a general index of  
38 catchment hydrological response. Among various applications, BFI has been implemented as an  
39 index of river flow regime classification ([Kennard et al., 2010](#); [Bejarano et al., 2010](#); [Olden and](#)  
40 [Poff, 2012](#)) and, as such, has also been used to detect hydrological regime changes along with other  
41 low flow indices ([Sawicz et al., 2014](#), [Coopersmith et al., 2014](#), [Crooks and Kay, 2015](#)).

42 Although the importance of the impact of geological catchment properties on BFI is universally  
43 understood ([Gustard et al., 1989](#); [Schneider et al., 2007](#); [Longobardi and Villani, 2013](#); [Zhang et al.,](#)  
44 [2013](#)), the role of climate variables is less clear ([Stoelzle et al., 2014](#); [Van Loon and Laaha, 2015](#),  
45 [Staudinger et al., 2015](#)). Recent global scale assessments of BFI patterns and the relevant influence  
46 of various climate factors have generally focused on average climate characteristics, such as the  
47 mean annual precipitation, mean annual potential evapotranspiration, mean annual air temperature,  
48 and the intra-annual seasonality of precipitation ([Beck et al., 2013](#); [Sawicz et al., 2014](#)).

49 A general agreement exists that climate (change or variability) has the potential to substantially alter  
50 river flow regimes. A global assessment has been reported in [Arnell and Gosling, 2013](#). At the  
51 European scale, a large body of literature provides indications regarding the considerable climate  
52 change projections that will impact hydrological systems. As a general trend, high latitude areas of  
53 northern Europe appear to face an increase in the number of wet days and thus a decrease in the  
54 duration of dry spells. Conversely, southern Europe Mediterranean areas appear to face a decrease  
55 in the number of wet days and thus an increase in dry spell duration ([Rajah et al., 2014](#); [Jacob et al,](#)  
56 [2014](#); [Pascale et al., 2016](#)). In a context where changes in climate are increasingly evident, it is  
57 important to study how the proportion of the slow component of flow is potentially affected by  
58 short-term rainfall properties.

59 The dry spell length and the catchment delay time, as well as their relative probability distributions,  
60 have in the past been considered to be primary descriptive parameters of the catchment hydrological  
61 response (Botter et al., 2013; Muller et al., 2014; Doulatyari et al., 2015). For example, Botter et al.  
62 (2013) showed how a combination of these descriptors can be used to determine the resilience of  
63 erratic and persistent regime systems to climate fluctuations. None of these studies, however,  
64 specifically focused on the baseflow component of the hydrograph. Therefore, in this study, we aim  
65 to illustrate the impact of climate variability and, in particular, the impact of dry spell duration on  
66 the baseflow process, summarized by the BFI index. We do this with a combined data-based and  
67 modelling study, investigating the hydrological behaviour of observed and virtual catchments that  
68 spanned a broad gradient of climate conditions and catchment properties.

69 In this study, two characteristic time scales were used, the dry spell length and the catchment delay  
70 time, to represent the effect of climate and catchment properties, respectively, on the BFI index.  
71 Investigated catchments were grouped into well-drained and poorly-drained systems based on their  
72 features. Catchments featured by perennial water resources, the well-drained group, were associated  
73 with prevailing slow streamflow components, large BFI values and long delays or recession times.  
74 Catchments with intermittent water resources, the poorly-drained group, were associated with fast  
75 prevailing streamflow components, small BFI values and short delay times.

76 To understand if both systems were affected by dry spell temporal variation to the same extent, a  
77 simulation approach was used where, given the generation of daily rainfall time series characterized  
78 by different average dry spell, the total discharge of the investigated catchments was computed in  
79 response to the generated rainfall scenarios, and BFIs were extracted by the application of a  
80 hydrograph filtering algorithm.

81 The primary findings of this study will help to elucidate the extent to which catchment properties  
82 can mitigate climate fluctuations and to determine which catchment properties are most meaningful  
83 for this purpose.

## 85 2. BFI ASSESSMENT FOR OBSERVED CATCHMENTS

### 86 2.1 Data description

87 Because the current investigation is focused on the impact of dry spell characterization on BFI  
88 assessment, the observed catchments were principally selected to provide a broad spectrum of  
89 climate conditions covered by a north-south European transect from extremely dry and seasonal  
90 types (typically in southern Europe) to temperate and oceanic types (typically in northern Europe).  
91 Moreover, because this study was concerned with BFI assessment, catchments were also selected to  
92 provide a broad range of BFI values and the correspondingly broad range of catchment delay times.  
93 According to these rules, daily streamflow, rainfall and temperature data were collated for 10  
94 catchments across Europe from local water agencies or as part of previous studies ([Brauer et al.,](#)  
95 [2011](#); [Van Lanen and Dijkma, 1999](#); [Van Huijgevoort et al., 2011](#); [Mehaiguene et al., 2012](#); [Van](#)  
96 [Loon and Van Lanen, 2013](#); [Longobardi and Villani, 2013](#)). The locations of the investigated  
97 catchments are indicated in [Figure 1](#).

98 Catchment areas vary between 6.5 and 16500 km<sup>2</sup>, and mean catchment elevation ranges between  
99 165 and 1060 m.a.s.l. The range of average annual precipitation is 347–1588 mm, with the largest  
100 values occurring for a humid region in southern Italy ([Longobardi et al., 2016](#)). Climate regime  
101 indications are provided with reference to the Köppen-Geiger climate classification ([Figure 1](#); [Peel](#)  
102 [et al., 2007](#)). A typical mean monthly rainfall distribution is provided in [Figure 1](#) for each of the  
103 investigated regions. Climate regimes range from dry type B to temperate type C classes. Semi-arid  
104 (Bsk) climates and Mediterranean climate conditions (Csa-Csb) are observed in the southern area of  
105 the investigated domain and are characterized by a rather marked seasonal distribution. Temperate  
106 oceanic climate conditions (Cfb) prevail in the northern area of the domain and are characterized by  
107 a more uniformly distributed precipitation regime. Average annual runoff ranges between 22 and  
108 1309 mm/yr, and none of the catchments shows important snow accumulation and melt processes.  
109 Bedrock permeabilities (derived from the Global Hydrogeology MAPs product; [Gleeson et al.,](#)  
110 [2014](#)) range between 10<sup>-4</sup> and 10<sup>-9</sup> m/s, ranging from high to extremely low values,. Soil types

111 range from podzols to cambisols to calcisols according to the FAO classification ([Soil Atlas of](#)  
112 [Europe, 2005](#)). More information is provided in [Table 1](#).

113

## 114 **2.2 Baseflow separation**

115 Hydrograph components separation was performed to assess the catchment long-term BFI.  
116 Following the definition of the Institute of Hydrology ([1980](#)), a BFI value was assessed as the ratio  
117 between the volume of baseflow and the volume of total streamflow; to derive the baseflow volume,  
118 baseflow separation was performed for each catchment.

119 At least three main categories of separation algorithms can be cited: empirical, digital filter-based  
120 and model-based techniques. Each procedure is, to a large extent, arbitrary ([Hewlett and Hibbert,](#)  
121 [1967](#)) but provides a repeatable methodology to derive objective measures or indices related to a  
122 particular streamflow source. Recursive digital filters (RDF) are the most commonly used methods  
123 for estimating baseflow because of their simplicity and quick implementation, which only needs  
124 streamflow data ([Eckhardt 2005; Aksoy et al., 2009; Li et al., 2014](#)), even though RDF parameters  
125 are questionable in certain cases, and geochemical or isotopic method calibration would improve  
126 the separation between slow and fast components ([Lott and Stewart, 2013; Longobardi et al., 2016](#)).  
127 Among RDFs, the Lyne and Hollick method ([Lyne and Hollick, 1979; Ladson et al., 2013](#)) seemed  
128 to be the most flexible approach and to have better performance for a wide range of climate  
129 conditions and catchment properties ([Li et al., 2014, Longobardi et al, 2016](#)). Because of these  
130 reasons, the Lyne and Hollick filter was selected for this study as a simple smoothing and  
131 separation rule to separate the baseflow from the total streamflow hydrograph. The Lyne and  
132 Hollick method acts as a low-pass filter to remove the high frequency quickflow component of  
133 streamflow from the low frequency baseflow component. The filter equation predicts the quickflow  
134  $q_q$  component at a time step  $t$  by

$$135 \quad q_q(t) = \alpha q_q(t-1) + \frac{1+\alpha}{2} [q(t) - q(t-1)], \quad (1)$$

136 subject to the restriction  $q_q > 0$ , where  $\alpha$  is the filter parameter that affects the degree of attenuation.

137 The baseflow component  $q_b$  at time step  $t$  is the difference between total streamflow  $q$  and

138 quickflow  $q_q$ :

$$139 \quad q_b(t) = q(t) - q_q(t), \quad (2)$$

140 subject to the restriction  $q_b \leq q$ . According to [Nathan and McMahon \(1990\)](#), the value of the filter

141 that yields the most acceptable results in term of baseflow separation is in the range of 0.9 to 0.95.

142 The filter was passed over the data three times, forward, backward and forward again, for a larger

143 smoothing effect, as suggested by [Nathan and McMahon \(1990\)](#).

144 The result of the assessment is illustrated in [Table 1](#). The BFI showed a large range for the studied

145 catchments, varying from 20% to 80%. The correlation between the BFI and catchment area (8%),

146 mean annual precipitation (3%) and mean annual runoff (3%) appears not relevant. Although not

147 significant, a larger positive correlation (43%) appeared between BFI and the permeability values

148 reported in [Table 1](#). Geo-hydrological soil properties are tightly related to the BFI, and the weak

149 numerical correlation extent found in the current analysis was probably because the permeability

150 values indicated in [Table 1](#) did not account for soil properties and were primarily derived from

151 bedrock type.

152

### 153 **3. CHARACTERISTIC SCALE IDENTIFICATION**

154 As discussed in the introduction, BFI vulnerability to dry spell length variation was investigated as

155 a function of two characteristic time scales: the catchment delay time “Ks” and the dry spell length

156 “d”. The first scale parameter helps to distinguish between catchments based on catchment

157 characteristics, particularly between poorly and well-drained catchments. The second scale

158 parameter helps to distinguish between catchments on the basis of climate characteristics. The

159 mentioned scales were identified by a modelling approach which was subsequently used to

160 investigate the mutual interaction between climate and catchment properties.

161

### 162 **3.1 Daily streamflow modelling**

163 In view of the modelling analysis that will follow, it is particularly interesting and also conceptually  
164 important to differentiate the catchments based on their hydrological response times. A high number  
165 and broad range of rainfall-runoff models are available for this aim. Popular physically based  
166 models were not considered in this study; simple conceptual approaches have instead been  
167 preferred, because although minimal in terms of model input and parametrization, they are able to  
168 capture catchment behaviour for highly different climate and basin properties. Among the  
169 conceptual rainfall-runoff models, the IAHCRES transfer function approach was selected ([Jakeman  
170 and Hornberger, 1993](#)). According to a large number of scientific papers, IHACRES appears to be a  
171 flexible and versatile model that has been applied to a very broad range of purposes from traditional  
172 streamflow prediction ([Razavi and Coulibaly, 2013](#)), water resources management ([Alredaisy,  
173 2011](#)), and water quality studies ([Letcher et al., 2002](#)) to reservoir operating rules management  
174 ([Ahmadi et al., 2014](#)). Studies exploring the role of climate changes and land cover changes on the  
175 hydrological response have also applied IHACRES ([Evans and Schreider, 2002](#); [Croke et al., 2004](#),  
176 [Aronica and Bonaccorso, 2013](#)).

177 The IHACRES model accounts for the non-linearity in the catchment response by a rainfall loss  
178 filter module driven by climatic forcing. Further down, a routing module considers the existence of  
179 two streamflow pathways, slow and fast, that contribute with different weights (time of delay and  
180 relative volumetric throughput) to total streamflow based on catchment characteristics. The  
181 conceptual separation between slow and fast paths enables the user to characterize the delay times  
182 for both streamflow components. The slow path delay time  $K_s$  was used in the current study to  
183 quantify the hydrological response characteristic time scale.

184 To test the ability of the model to describe the catchment hydrological behaviour under the climate  
185 and geology gradient considered in this study, the model was applied to the 10 catchments under  
186 investigation and its performance was measured in terms of the following statistics. Slow flow  
187 component delay time ( $K_s$ ) and slow flow component volumetric throughput coefficient ( $v_s$ ) are

188 illustrated in [Table 2](#). Statistics used to measure model performance were the NSE (Nash and  
189 Sutcliff Efficiency coefficient), the coefficient of determination ( $r^2$ ), the LNSE (Nash and Sutcliffe  
190 Efficiency with logarithmic values), and d (index of agreement; [Willmott et al., 1985](#)). Because the  
191 catchment vulnerability to dry spell length variability was quantified in terms of long-term BFI  
192 changes, it was important to understand how reasonable the BFI values provided by the modelling  
193 approach were. To quantify such a feature,  $BFI_{cal}$ , the BFI value obtained by filtering the modelled  
194 time series after calibration, and the BFI relative error percentage between the BFI (computed for  
195 observed time series) and  $BFI_{cal}$  were also estimated. Metrics estimation is provided in [Table 2](#).  
196 Overall model performance appeared rather satisfactory. Average NSE was approximately 0.7 (min  
197 0.67), average  $r^2$  was approximately 0.85 (min 0.81), average LNSE was approximately 0.66 (min  
198 0.45) and average D was approximately 0.73 (min 0.63). The relative percentage error between the  
199 BFI computed for the observed time series and the  $BFI_{cal}$  computed for the modelled time series  
200 was negligible with an average value of approximately 6%. There was no systematic bias in the BFI  
201 model results with both positive and negative deviations from observed values ([Table 2](#)) The need  
202 to use a specific simulation approach that provided optimal results for the different climate and  
203 catchment property conditions was considered and thus appears to be congruent with the selected  
204 model.

205

### 206 **3.2 Daily rainfall modelling**

207 The characteristic time scale for climate settings is the dry spell  $d$ , the period between two  
208 consecutive rainfall occurrences. A stochastic point process approach was adopted to describe and  
209 assess the characteristic time scale for each of the investigated catchments and for the subsequent  
210 generation of daily rainfall series to be used as inputs in the following simulation analysis. The  
211 daily rainfall time series were modelled as stochastic Poisson processes with rectangular pulses  
212 (PRP) ([Rodriguez-Iturbe et al., 1987](#)). The arrival times of daily rainfall storms were assumed to  
213 follow a Poisson process of rate  $\lambda$  such that the dry spells were independently and identically

214 distributed as exponential random variables with mean  $d=1/\lambda$  days. Rainfall intensity at time  $t$  was  
215 obtained as the sum of intensities of all overlapping storms that occurred at that time, which could  
216 be generated for each storm occurrence marked by the Poisson process. Rainfall intensity had an  
217 exponential distribution with parameter  $\mu$ .

218 Average  $d$  duration for the studied catchments ranged between a minimum of approximately 3 days  
219 (HUP - Cfb) and a maximum of approximately 14 days (PLA - Csa) from northern to southern  
220 latitudes (Table 3). Rainfall intensity ranged between approximately 1 mm/d (DJE - Bsk) and 4.36  
221 mm/d (BUS – Csa, Csb), with a relatively lower dependence on a catchment's geographical  
222 coordinates (Table 4).

223 For the successive simulation analyses it was important to confirm the suitability of the PRP  
224 approach for the case studies. To assess the goodness-of-fit for the studied data, main descriptive  
225 statistics (mean, maximum, standard deviation) for observed and modelled daily rainfall were  
226 quantified and are reported in Table 3 and Table 4. Additionally, observed and modelled daily  
227 rainfall cumulative distributions were compared with the use of the average absolute percentage  
228 error (AAPE), defined as

$$229 \quad AAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{F_{obs,i} - F_{mod,i}}{F_{obs,i}} \right| \quad (3)$$

230 where  $i$  is the percentile order,  $F_{obs,i}$  is the cumulative distribution for observed daily rainfall  
231 corresponding to the  $i$ -th percentile,  $F_{mod,i}$  is the cumulative distribution for modelled daily rainfall  
232 corresponding to the  $i$ -th percentile, and  $n$  is the number of percentiles. AAPE values are also  
233 reported in Table 3 and Table 4.

234 Overall model performance appears to have been rather satisfactory. The  $d$  process, which is of  
235 particular interest in the current research, appears to have been well represented. Errors in  
236 cumulative distribution fitting were smaller than 10% for half of the catchments and not larger than  
237 25% for the remaining catchments (Table 3). Beyond mean values, the maximum values for dry

238 spell length also appeared congruent with the observations (Table 3). Similar comments hold for the  
239 rainfall intensity, with a moderate increase in the goodness-of-fit errors (Table 4).

240

#### 241 **4. THE RELATION BETWEEN OBSERVED CATCHMENT BFI, CATCHMENT DELAY** 242 **AND DRY SPELL**

243 For the number of investigated catchments, Ks ranged between approximately 30 days (HUP) to  
244 200 days (NOO), as reported in Table 2. When BFI values were plotted against Ks values,  
245 catchments appeared to have been naturally forced into two clusters as indicated in Figure 2, where  
246 the empirical relation between Ks and BFI is illustrated.

247 The well-drained group was characterized by a delay time longer than 80 days and BFI values  
248 larger than 0.5. Within this group, the empirical relationship Ks-BFI showed increasing BFI for  
249 increasing delay times. Larger Ks (larger BFI) values generally occurred for high permeability  
250 and/or high water holding capacity soils (Table 1). The poorly-drained group was characterized by  
251 delay times shorter than 80 days and BFI values smaller than 0.5. For this group, the empirical  
252 relationship Ks-BFI was not as evident as in the well-drained one because catchments having  
253 similar response delay times were associated with very different BFI values. For example, the Platis  
254 (PLA) and Hupsel (HUP) catchment delay times were approximately 44 days and 30 days,  
255 respectively, but the BFI for HUP was 50% larger than the BFI for PLA. Lower Ks (lower BFI)  
256 values were generally associated with low permeability and low water holding capacity soils (Table  
257 1).

258 The empirical relationship between d and the BFI was less clear because the same values of d  
259 related to extremely different BFI values (Figure 3). Groups were indeed still noticeable, but they  
260 were primarily driven by the BFI value, and poorly-drained catchments lay respectively above and  
261 below the threshold of BFI = 0.5. Within each group, although it was more evident for the well-  
262 drained group, a more uniform precipitation distribution represented by a small value of d, typical  
263 in medium to northern latitude climates, related to larger BFI. As an example, the Platis (PLA) and

264 Hupsel (HUP) difference in BFI assessment previously cited seems to be justified by their relative d  
265 values; the Hupsel catchment was indeed forced by more uniform precipitation occurrences, which  
266 made the related hydrological regime more persistent and subsequently yielded a larger BFI value  
267 compared with the Platis catchment.

268 The coevolution of climate and geology is not new to the scientific literature (Troch et al., 2015).  
269 Both at plot and regional scales, climate features control soil development and soil properties  
270 (Lavee et al., 1997) to the point that climate changes are supposed to affect and induce changes in  
271 hydro-geomorphological processes (Lane, 2013). Catchment delay times are frequently considered  
272 as constant parameters and related to catchment properties; however, for a more realistic simulation,  
273 particularly of the baseflow time series, concern has been raised about a dependence on the climate  
274 regime properties (He et al., 2016; Longobardi et al., 2016). The dataset used for the current  
275 analysis empirically depicts such a relation, although it represents a small sample (Figure 4).  
276 Although rather scattered, a tendency seems to appear in Figure 4 where the larger the d, the smaller  
277 the Ks (the less uniform the precipitation regime, the less persistent the hydrological regime). The  
278 Hupsel catchment represents an exception to the rule, probably because of the combination of very  
279 low permeability and small drainage area.

280 Soil and geological properties and climate effects on the baseflow properties could be individually  
281 considered only to a limited extent because they have the potential to impact each other and  
282 mitigate the relevant effects. To summarize their mutual impact on the BFI, the ratio between the  
283 characteristic time scales could be considered, that is,  $d/K_s$ .

284 If the BFI is in fact plotted against the  $d/K_s$  values, the existence of well- and poorly-drained groups  
285 resulted in an almost univocal relation, such as for the case of Ks dependence (Figure 2); however,  
286 in this case, the impact of d was also considered (Figure 5). In fact, this pattern enabled the group  
287 definitions to be maintained and the BFI values to be sorted as an inverse decreasing function of  
288  $d/K_s$ . Large  $d/K_s$  values defined the domain of catchments where d and Ks were of the same order  
289 of magnitude. Poorly-drained catchments were located in this section with BFI values of

290 approximately 25%. Inversely, low  $d/K_s$  values defined the domain of catchments where  $d \ll K_s$ .  
291 Well-drained catchments were located in this section, with a BFI larger than 60% being observed.  
292 The use of the ratio  $d/K_s$  in the description of the BFI variability also quantitatively strengthens the  
293 dependence of this index on the characteristic time scales identified. By using a regression model to  
294 explain the variability of the BFI with respect to the  $K_s$  parameter alone, we find that the variance  
295 explained is very high in the case of the well-drained group (85%) and very low in the case of the  
296 poorly-drained group (22%). Using instead the ratio  $d/K_s$ , the variance explained with respect to the  
297 whole set of basins is equal to 85%.  
298 If the introduction of the weight  $d$  on  $K_s$  does not appear significant for the well-drained group, it  
299 made it possible to distinguish between poorly-drained catchments with the same hydrological  
300 properties but different climate parameters.  
301 The representation provided in [Figure 5](#) justifies indeed the previously mentioned observed  
302 differences between HUP and PLA, assigns them significantly different  $d/K_s$  ratios, and embeds the  
303 significant differences in terms of  $d$ .

304

## 305 **5. MODELLED IMPACT OF DRY SPELL DURATION ON OBSERVED CATCHMENT**

### 306 **BFI**s

307 Next we used a simulation approach to measure how changes in dry spell length propagate through  
308 the catchment response to produce changes in the BFI values. Changes in  $d$  included both a  
309 decrease (wetter conditions) and an increase (drier conditions) in  $d$ . Each of the catchments in [Table](#)  
310 [1](#) is characterized by a deterministic catchment response; the hydrological model parameters ([Table](#)  
311 [2](#)) were thus kept constant, as well as the slow path delay time  $K_s$ . For each of the catchments,  
312 several daily rainfall scenarios were generated according to the PRP model, each characterized by a  
313 different value for  $d$ . The parameter range for  $d$  was based on the empirical study, which covered an  
314 exhaustive gradient of climate conditions. The average daily  $d$  was assumed to vary between 3 and

315 16 days To compare catchments, only increases or decreases of 20% and 50% of the initial  $\bar{d}$  value  
316 were considered in the modelling exercise (Figure 6).

317 Generated rainfall scenarios were then used to force the IHACRES model to simulate the catchment  
318 response, and the Lyne and Hollick algorithm was used to derive the baseflow series from the  
319 simulated total streamflow series to quantify the BFI index. Overall, an increase in  $\bar{d}$ , that is a shift  
320 towards drier conditions, led to a decrease in the BFI ( $\Delta_{dry}$ ); in contrast, a decrease in  $\bar{d}$ , that is a  
321 shift towards wetter conditions, led to an increase in the BFI ( $\Delta_{wet}$ ). Catchment vulnerability was  
322 measured by

$$323 \text{ maximum percentage BFI increase} = \frac{\Delta_{wet}}{BFI_{\bar{d}}} = \frac{BFI_{\bar{d}^{-\%}} - BFI_{\bar{d}}}{BFI_{\bar{d}}} (\%) \quad (4)$$

324 and

$$325 \text{ maximum percentage BFI decrease} = \frac{\Delta_{dry}}{BFI_{\bar{d}}} = \frac{BFI_{\bar{d}} - BFI_{\bar{d}^{+\%}}}{BFI_{\bar{d}}} (\%) \quad (5)$$

326 where  $\bar{d}$  represents the initial  $\bar{d}$  value,  $\bar{d}^{-\%}$  represent the 20% (or 50%) reduced value for  $\bar{d}$  and  $\bar{d}^{+\%}$   
327 represents the 20% (or 50%) increased value for  $\bar{d}$ . In the following, we only considered as  
328 significant a variation in BFI larger than 10%.

329 The behaviour of poorly-drained and well-drained groups was different, and the main findings are  
330 summarized below.

331 A 20% decrease in  $\bar{d}$  values did not produce changes in BFI for any of the studied catchments, a  
332 50% decrease generated BFI increases up to 20% (Figure 7 – left panel). Poorly-drained catchments  
333 appear the most vulnerable as they are associated with the largest maximum percentage BFI  
334 increases. Within this group, catchments with a combination of small  $K_s$  and large  $\bar{d}$  (large  $\bar{d}/K_s$   
335 values) appear to be the most affected (Figure 7 c)). Catchments located at the opposite boundary,  
336 low  $\bar{d}/K_s$  (large  $K_s$  and small  $\bar{d}$ ), were almost unresponsive to a decrease in dry spell length. The  
337 same could be said in the case of a shift toward wetter condition, where 20% and 50%  $\bar{d}$  increases  
338 generated almost similar effects on the studied catchments (Figure 7 – d), e) and f)).

339 The unexpected behaviour of some catchments in this analysis can be explained by soil properties.  
340 This is for example the case of the Sele watershed, SEL, which is among the class of well-drained  
341 the only catchment to be significant affected by variation in  $d$  (Figure 7 c)). Although in the group  
342 classification based on  $K_s$  SEL clearly belongs to the well-drained group (Figure 2), if the  $d/K_s$   
343 ratio is used, SEL lays in the  $d/K_s$  range typical for the poorly-drained group (Figure 5). Different  
344 from the other well-drained catchments, SEL bedrock permeability was not very large, and the large  
345 BFI value (0.54), which forces SEL into the well-drained group, was probably generated by the  
346 presence of very important alluvial deposits, rather than by large bedrock permeability. Soil  
347 properties can also explain the difference between the Djidiouia (DJE) and Platis (PLA) watersheds  
348 (Figure 7 f)). Characterized by similar values for  $K_s$  and  $d$  (and consequently  $d/K_s$ ) and by the same  
349 bedrock permeability (Table 1), PLA and DJE differed in terms of soil types, which were leptosols  
350 and calcisols, respectively. The capacity of leptosols to hold water and contribute to baseflow  
351 generation is low, which may have led to the BFI decrease detected by the simulation

352

## 353 **6. INFLUENCE OF DRY SPELL DURATION ON BFI IN SIMULATED VIRTUAL** 354 **CATCHMENTS**

355 To support and further expand the results provided by the analysis of the observed catchments, the  
356 hydrological behaviour of a very broad set of virtual catchments was investigated.

357 The observed catchments selected for the current study covered a broad spectrum of climate  
358 conditions, ranging from extremely dry and seasonal climate types to temperate and oceanic climate  
359 types. The catchments also covered a broad range of BFI values and corresponding catchment delay  
360 times (tightly related to BFI as shown in Figure 2). Assuming that the selected catchments cover the  
361 range of hydrological catchment behaviours existing in Europe, the maximum and the minimum  
362 values of the PRP and IHACRES model parameters calibrated for the observed catchments were  
363 used as the range of model parameters (both PRP + IHACRES) in the synthetic simulation. These  
364 simulations were used to generate synthetic streamflow time series for above two thousand “virtual

365 catchments” (Table 5). The virtual catchment behaviour was studied in terms of BFI assessment  
366 and its variability with the  $d/K_s$  parameter.

367 Although a good correspondence was found between observed and virtual catchments, the BFI- $d/K_s$   
368 domain described by the virtual catchments (Figure 8) extended beyond the range of the observed  
369 catchments, which strengthened the significance of the findings, especially concerning the  $d/K_s$   
370 parameter.

371 According to Figure 8 (upper right panel), for a given  $d$  value, the effects of  $K_s$  on the BFI was  
372 practically negligible for the poorly-drained group; a long and narrow tail in the BFI- $d/K_s$  domain  
373 was recognized for large  $d/K_s$  values, which corresponded to the lower range for  $K_s$ . The effect  
374 became more important for the well-drained group because the spread of the BFI- $d/K_s$  domain  
375 significantly increased from larger to smaller  $d/K_s$ .

376 For a given value of  $K_s$  (Figure 8 right lower panel) the effect of  $d$  on the BFI assessment, measured  
377 by the width of the domain, appeared important for the well-drained group (lower  $d/K_s$  values) and  
378 particularly for values included in the interval 0.1-0.3, where the extent of the domain appeared  
379 wider. The importance of  $d$  on BFI assessment was drastically reduced for the poorly-drained group  
380 (large  $d/K_s$  values, larger than 0.6), for which BFI values were within the minimal range of 0.1-0.2  
381 regardless of the  $d$  values.

382 Similarly to what represented for the observed catchments in Figure 7, Figure 9 illustrates the  
383 maximum percentage BFI increase or decrease for the dataset of virtual catchments due to a  
384 decrease and an increase in the dry spell length. The results found for the virtual catchments appear  
385 congruent with the finding from observed catchments. A 50% decrease in  $d$  produces larger effect  
386 than a 20% decrease, whereas the effect of a 20% and a 50% increase are similar in terms of BFI  
387 changes. Larger changes are also in this case detected for large  $d/K_s$ .

388 It has to be noted however that the use of a percentage decrease or increase of the initial value of  $d$ ,  
389 e.g., 20% and 50%, considered in the current analysis, implies that systems characterized by small  
390 initial  $d$  values see a smaller absolute change in  $d$  (and  $d/K_s$ ) than systems characterized by a large

391 value of initial  $d$ . As an example, [Figure 10](#) shows the modelled BFI variability for a set of virtual  
392 catchments featured by two extremely different initial  $d$  values and subject to the same 50%  $d$   
393 decrease. Systems featured by the same  $K_s$  values exhibit a significantly different behaviour  
394 depending on their initial state. In the case of the lower  $K_s$  (the poorly-drained group) starting from  
395 a dry initial condition (large  $d$ ) leads to a 30% overestimation of BFI variability compared to the  
396 case of wet initial conditions (red boxes in [Figure 10](#)). Differences are evidently dampened in the  
397 case of large  $K_s$  (the well-drained group, blue triangles in [Figure 10](#)). The range of variability of the  
398  $d/K_s$  parameter is furthermore significantly larger in the case of initial dry conditions.

399 As this effect might distort the assessment of the impact of  $d$  variability on the BFI, the maximum  
400 BFI increase and decrease were standardized by a measure of variability of the  $d/K_s$  index, the  
401 standard deviation of the  $d/K_s$  ([Figure 11](#)). The simulation experiments showed that, even though  
402 under the same dry spell variation, the BFI vulnerability appeared higher for catchments poorly-  
403 drained systems, attributing an equal weight to the variations in  $d$  both in the case of dry and wet  
404 initial conditions, for tendencies towards both wetter and drier climates, the poorly-drained systems  
405 appear to have been less impacted by climate fluctuation than the well-drained systems.

406 To further support the results, the BFI vulnerability can be additionally studied in terms of BFI  
407 variability, the BFI standard deviation, beyond the maximum percentage increase/decrease. [Figure](#)  
408 [12](#) indicates even more clearly how the impact on BFI variability decreases for large  $d/K_s$  ratios,  
409 thus for the poorly-drained group. In particular the maximum variability in standardised BFI was  
410 approached for a  $d/K_s$  values that correspond to the limit of transition between the well-drained and  
411 the poorly-drained groups as illustrated for the observed catchments in [Figure 5](#).

412

## 413 **7. CONCLUSIONS**

414 In a combined data-based and modelling study, where the hydrological behaviour of observed and  
415 virtual catchments was investigated over a broad gradient of climate conditions and catchment

416 properties, we aimed to illustrate the impact of climate variability and, in particular, the impact of  
417 dry spell duration on the baseflow process, as summarized by the BFI index.

418 An index based on the combination of catchment and rainfall properties,  $d/K_s$ , the ratio between the  
419 dry spell length and the catchment delay time, was used to group catchments into well- and poorly-  
420 drained groups and to measure the variability of the BFI index for a given rate of dry spell  
421 variability.

422 As a general rule, the effect of the main hydrological parameter  $K_s$  on the BFI was practically  
423 negligible for the poorly-drained group and became more important for the well-drained group as  
424 the spread of the BFI- $d/K_s$  domain significantly increased from larger to smaller  $d/K_s$ . The impact  
425 of  $d$  on the BFI, as measured by the width of the domain BFI- $d/K_s$ , appears to be important for the  
426 well-drained group (lower  $d/K_s$  values) and drastically reduced for the poorly-drained group (large  
427  $d/K_s$  values, larger than 0.6), for which BFI values were set to minimal values regardless of the  $d$   
428 values.

429 With respect to the climate fluctuation and in particular an increase or decrease in dry spell length,  
430 the tendency towards drier climates (extension of dry spell length) appears to have caused minor  
431 hydrological impact, compared with the tendency towards wetter climates. The simulation  
432 experiments further showed how, for tendencies towards both wetter and drier climates, the poorly-  
433 drained systems appear to have been less impacted by climate fluctuation than the well-drained  
434 systems and that the impact reached maximum values for systems laying in the transition zone  
435 between well- and poorly-drained systems.

436 Although the virtual catchment behaviour enabled the assessment of general patterns of BFI  
437 vulnerability, the study of the observed catchments provided a thorough knowledge of the  
438 hydrological systems and shed light on the role of specific hydrological parameters, that is, the  
439 catchment properties, on BFI assessment.

440 It is important to stress that the reported effects on the BFI variability produced by the variability in  
441 the dry spell length do not represent the impact of climate variations on the full spectrum of the low

442 flow hydrological regime but on only one of the indices to be used to classify the low flow regime.  
443 Being a long-term average index, the BFI is probably moderately sensitive to changes towards  
444 more-or-less extreme climate conditions, but it is not insensitive, and future research on indices that  
445 describe more extreme low flow features could show even more marked results.

446

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573

574 **Figure captions**  
575

576 Figure 1: Red frames indicate regions where the investigated catchments are located. Histograms of mean  
577 monthly rainfall distribution are illustrated for each region. The Köppen climate classification map  
578 is also provided (upper right corner) for identification of climate groups.

579 Figure 2: BFI dependence on slow storage delay times. Squares define poorly-drained and circles define  
580 well-drained catchments.

581 Figure 3: BFI dependence on average dry spell  $d$ . Squares define poorly-drained and circles define well-  
582 drained catchments.

583 Figure 4: Empirical relationship between average dry spell  $d$  and slow storage delay time. Squares define  
584 poorly-drained and circles define well-drained catchments.

585 Figure 5: BFI dependence on  $d/K_s$  ratio. Squares define poorly-drained and circles define well-drained  
586 catchments.

587 Figure 6: Modelling analysis flow chart.

588 Figure 7: Maximum percentage BFI decrease or increase as a function of  $d$ ,  $K_s$  and  $d/K_s$ . Squares define  
589 poorly-drained and circles define well-drained catchments. Light colours define 20% increase or  
590 decrease in  $d$ ; dark colours define 50% increase or decrease in  $d$ . Right panel: dry spell length  
591 increase. Left panel: dry spell length decrease.

592 Figure 8: BFI- $d/K_s$  domain for observed (red circles) and virtual catchments (light blue circles). The insets  
593 visualizes the effect of model parameters on the spread of the results. Right upper panel: effect of  
594  $K_s$ . Right lower panel: effect of  $d$ .

595 Figure 9: Maximum percentage BFI increase (left panels) and decrease (right panels) as a function of  $d/K_s$ .  
596 Light colours (upper panel) define 20% decrease or increase in  $d$ ; dark colours (lower panel) define  
597 50% decrease or increase in  $d$ .

598 Figure 10: Modelled BFI variability induced by a decrease in  $d$  of 50% in the case of dry initial conditions (large  $d$ )  
599 and wet initial conditions (small  $d$ ). Virtual catchments inside red and blue boxes are characterized by the  
600 same  $K_s$  value.

601 Figure 11. Ratio between BFI maximum percentage increase and decrease and  $d/K_s$  standard deviation for a  
602 decrease (left panels) and an increase (right panels) of the dry spell length  $d$ . Light colours (upper  
603 panel) define 20% decrease or increase in  $d$ ; dark colours (lower panel) define 50% decrease or  
604 increase in  $d$ .

605 Figure 12: Ratio between BFI standard deviation and  $d/K_s$  standard deviation for a decrease (left panels) and  
606 an increase (right panels) of the dry spell length  $d$ . Light colours (upper panel) define 20% decrease  
607 or increase in  $d$ ; dark colours (lower panel) define 50% decrease or increase in  $d$ . Plot areas  
608 included in the red boxes are enlarged in the adjacent illustrations.