

1 **Hydro-geo-chemical streamflow analysis as a support for digital hydrograph filtering in a small,**
2 **rainfall dominated, sandstone watershed**

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30 **Abstract**

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32 The aim of the present study is an analysis of the ability of digital hydrograph filtering tools for the
33 characterization of the baseflow source contributing to total streamflow for a typical, small, sandstone,
34 rainfall dominated catchment. Daily streamflow and electrical conductivity data for an experimental
35 catchment, the Ciciriello catchment, a 3km² watershed located in Southern Italy, have been collected to
36 the purpose since 2012. The application of a mass balance filter (MBF), using electrical conductivity as
37 tracer data, has pointed out a seasonal characterization of the baseflow pattern, contributing to total
38 streamflow by 90% during the low flow period and up to 40% during the high flow period. The Lyne and
39 Hollick one parameter and the two parameters Eckhardt digital filters have been furthermore processed,
40 both in an uncalibrated and calibrated application. Providing a preliminary total streamflow and baseflow
41 recession analysis, the one parameter filter appears particularly suited for ungauged cases, as the
42 uncalibrated and calibrated applications are almost identical, with relative prediction errors, compared to
43 MBF, smaller than 5%. The uncalibrated two parameters filter generates instead large relative error of
44 about 35%. To improve the baseflow description, in particular during the low flow period, and to correct
45 large (28%) underestimation of the minimum baseflow value, a seasonal calibration for the BFI_{max}
46 parameter (the maximum BaseFlow Index that can be modelled by the filter algorithm) is in fact needed.

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48

49 **Keywords:** hydrograph filtering, electrical conductivity, recursive digital filter, Mediterranean, Cilento

50 UNESCO Global Geopark.

51 **1. Introduction**

52 The baseflow represents the slow streamflow component and it is generally related to groundwater
53 outflows from shallow and deep aquifers, as in fact, regardless for the specific climate environment, its
54 main features are tightly related to geological catchment properties (Mwakalila et al., 2002; Bloomfield et
55 al., 2009; Mehaiguene et al., 2012; Longobardi and Villani, 2013; Ahiablame et al., 2013). Understanding
56 the baseflow process is useful in many different water related issues, from water resources management
57 strategies, low-flow conditions assessment, hydrological modelling calibration to water quality studies.
58 Despite its importance, measurements of baseflow are actually unavailable, thus, hydrograph filtering
59 approaches help to overcome this deficiency, providing a quantitative assessment of the slow streamflow
60 component.

61 Hydrograph separation has been defined in the past as “one of the most desperate analysis techniques in
62 use in hydrology” (Hewlett and Hibbert, 1967). In spite of a very broad number of experimental and
63 analytical studies and of relevant scientific advances, the procedures available to this purpose are indeed
64 still arbitrary, especially because the subjective influence of the user could impact the results (Rimmer
65 and Hartmann, 2014). However, they provide a repeatable methodology to derive objective measures or
66 indexes related to a particular streamflow source.

67 Several approaches are reported in the scientific literature for hydrograph filtering purposes. These can be
68 grouped into analytical, empirical and mass balance methods (Stewart, 2015). Analytical methods are
69 based on the fundamental theories of groundwater storage, often assuming ideal conditions that may not
70 always be true (Boussinesq, 1877). Among others, empirical approaches have found considerable success:
71 they are mainly based on a modelling framework, for which calibration is needed, based on field
72 measurements or simply based on the user experience. Among these, a large number of recursive digital
73 filters, assuming that the baseflow is the smooth frequency component of total hydrograph, have been
74 proposed in the past literature (Lyne and Hollick, 1979; Nathan and McMahon, 1997; Chapman, 1999;
75 Eckhardt, 2005; Aksoy et al., 2009). The mass balance methods are instead based on the assumption that
76 baseflow has different chemical characteristics compared with surface runoff, because of the different
77 residence times and flow paths of these two sources. Compared to others, the mass balance filtering
78 method is considered to be an objective approach, because it is based on basin-specific physical processes
79 and relevant monitoring activities. A wide use has been gained from the electrical conductivity used as

80 tracer for different water sources ([Pinder and Jones, 1969](#); [Lott and Stewart, 2013](#); [Li et al., 2014](#);
81 [Longobardi et al., 2015](#)). Electrical conductivity monitoring campaigns have been also successfully
82 exploited for purpose of digital filter calibration ([Stewart et al., 2007](#); [Zang et al., 2013](#); [Cartwright et al.,](#)
83 [2014](#)).

84 Even though able to separate a more realistic and plausible baseflow pattern, compared to more empirical
85 methodologies, digital recursive filters still do not consider the hydrological phenomena behind the
86 baseflow production and are disconnected from climate features which would however impact the
87 baseflow generation ([Furey and Gupta, 2001](#); [Eckhardt, 2008](#); [He et al., 2016](#); [Lott and Stewart, 2016](#)). In
88 addition, the potential for their use has not yet been fully explored for particular hydro-geomorphological
89 units, in particular for hard rock and rainfall-dominated catchments, for which there is a need to
90 understand whether they are actually appropriate for such type of catchments ([Eckhardt, 2005](#)).

91 Focused on the relation between the geodiversity and ecosystem characteristics in the Cilento, Vallo
92 Diano and Alburni National Park headwaters, a research program was launched in 2012. The program,
93 currently granted by the UNESCO Cilento Global Geopark, promotes the monitoring activities performed
94 in reference catchments, significant for the hydro-geodiversity of the sandstone landscapes, in the
95 perspective of a progressive extension of the research tasks to similar catchments in other protected areas
96 and Geoparks of the Mediterranean basin. Within this program, a 3km² drainage area, the Ciciriello
97 catchment, has been instrumented to collect data to enhance the knowledge of the hydro-
98 geomorphological behaviour of sandstone and forested units ([Cuomo and Guida, 2013](#)). Beyond
99 traditional meteorological and streamflow measurements, geochemical properties have also been
100 monitored, providing an objective approach to analyse the ability of digital hydrograph filtering tools for
101 the characterization of the baseflow source contributing to total streamflow for small, rainfall dominated
102 catchment, typical for sandstone landscapes. For the purpose, two different low-pass recursive digital
103 algorithms have been selected, featured by an increasing level of flexibility and filter parameters. These
104 are the [Lyne and Hollick \(1979\)](#) one parameter filter and the two parameters [Eckhardt's filter \(2005\)](#). The
105 comparison with the mass balance approach will help addressing the selection of the most appropriate
106 method for baseflow separation in case of poorly gauged catchments, for which tracer data are not
107 available. An objective calibration of filter model parameters will furthermore address the ability of the

108 filters to adapt to markedly variable hydrological regimes resulting by markedly variable climate
109 conditions.

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111 **2. The Ciciriello experimental catchment**

112 2.1 The experimental watershed

113 The Ciciriello Watershed (LAT 40.1957 LONG 15.5379) is located in the southeast of Campania,
114 Southern Italy. The area of the watershed is about 3km² and it is a dominantly forested area, without
115 relevant human impacts. Elevation in the watershed ranges from 420 to 812 (M. Marchese) meters above
116 mean sea level. The climate of the region is humid Mediterranean. Annual average precipitation is about
117 1400 mm with a marked difference between average maximum monthly summer precipitation, of about
118 30 mm, and average maximum monthly winter precipitation, of about 250 mm (Blasi et al., 2013).

119 From a hydro-geomorphological point-of-view, the Cilento and Vallo di Diano Geopark (Figure 1)
120 consists of carbonate, sandstone and alluvial aquifers (Allocca et al., 2014). Sandstone aquifers, despite
121 their great local interest in ecological issues, traditional agriculture and forestry maintenance, have had so
122 far less attention than karst carbonate systems. Due to the lack of complete knowledge about the
123 hydrological behavior of sandstone catchments within the Cilento and Vallo di Diano Geopark, the
124 Ciciriello watershed has been chosen as an experimental catchment.

125 In the watershed, a southwestern dipping sandstone aquifer is resting in unconformity on a folded strata
126 marly-clayey aquiclude. Along the western valley side, inter-bedded to the sandstone strata, a 10 m-thick
127 lenticular marly bed outcrops (Figure 2). The bedrock is covered by thick regosols on the upper ridges,
128 regolith on the noses and spurs and gravelly slope deposits at the toe of the open slopes. The stream bed is
129 incised in alluvial, coarse deposits and partly on bedrock. Colluvium hollows are located in the bottom of
130 the zero order basins. Permanent springs from bedrock aquifers and seasonal outflows from shallow,
131 perched aquifers and colluvium deposits increase, progressively downstream, the stream discharge.

132 2.2 Data collection

133 Since December 2012, and currently in progress, a number of monitoring stations have been located along
134 the drainage network of the Ciciriello watershed. The main station is located at the outlet of the catchment
135 (420 m a.s.l.). In addition, secondary stations have been located just upstream from the main tributary
136 junctions and downstream from the perennial bedrock springs and temporary seasonal through flow

137 outlets from the zero order basins (Figure 2). Location and timing of the monitoring activity have been
138 based on detailed, multi-temporal hydro-geomorphological surveys and measurements, oriented by the
139 “variable source areas” concept (Hewlett and Hibbert, 1967) and the “hydro-geomorphic paradigm”
140 (Sidle et al., 2000).

141 Water depth (D), discharge (Q) and electrical conductivity (EC) have been measured, daily, at main
142 station and, weekly, at the sub-stations. The Swoffer 3000 current meter (Swoffer Inc., USA) has been
143 used for discharge measurements, and the HI9828 multi-parametric probe (Hanna Instruments Inc.,
144 Romania) for EC measurements. During selected storm events, 10-minute D and EC data have been
145 moreover recorded at the main station by using the data logger DL/N70-Multi (STS Inc., Switzerland).
146 Rainfall and temperature data, at 10-minute time resolution, for Sanza rain gauge have been provided by
147 courtesy of the Civil Protection Service of the Campania Region.

148

149 **3. Baseflow component characterization through mass balance approach**

150 Monitored electrical conductivity data have been used for the application of a mass balance filter
151 algorithm (MBF) to provide an objective description and characterization of the baseflow pattern and
152 indices for the Ciciriello watershed. The objective MBF separation also enables highlighting similarities
153 and differences in the hydrograph recession process for total and baseflow time series, useful for the
154 following additional hydrograph separation applications.

155 3.1 Mass Balance Filtering (MBF)

156 The mass balance method is based on the assumption that baseflow has different chemical characteristics
157 compared with surface runoff due to the different flow paths of these two types of flows. As a
158 consequence, total streamflow hydrograph can be separated into different components on the base of the
159 single component concentration. Mass balance, using the electrical conductivity EC as proxy of the Total
160 dissolved solids (TDS), is one of the most widely used tracer technique. Total dissolved solids (TDS), in
161 milligram/liter (ppm) and electrical conductivity (EC) in microSemiens/centimeter ($\mu\text{S}/\text{cm}$) are related by
162 a conversion factor TDS/EC variable between 0.5-0.7, depending on which type of conversion is used,
163 respectively, the NaCl conversion (sodium chloride) or the 442 conversion (40% sodium sulfate, 40%
164 sodium bicarbonate, and 20% sodium chloride) (Atekwanaa et al (2004).

165 The baseflow component, in non-evaporitic terrains and unglaciated landscapes, has generally greater EC
 166 values compared to the surface runoff conductivity and, for this reason, EC can be used as a natural tracer
 167 of the streamflow component. This behaviour is particularly evident in the hydro-chemograph illustrated
 168 in [Figure 3](#), where the measured EC approaches the largest values during the low flow period,
 169 corresponding to the period from early summer to late autumn in the humid Mediterranean climate,
 170 according to [Cuomo and Guida \(2016, under revision\)](#). It is possible to consider the following equations
 171 system (MBF):

$$172 \left\{ \begin{array}{l} q_{tot}(t) = q_{sf}(t) + q_{bf}(t) \\ q_{tot}(t) \cdot EC_{tot}(t) = q_{sf}(t) \cdot EC_{sf}(t) + q_{bf}(t) \cdot EC_{bf}(t) \end{array} \right. \quad (1)$$

173 where

174 q_{tot} = measured total streamflow (l/s); q_{sf} = surface streamflow component (l/s); q_{bf} = baseflow streamflow
 175 component (l/s); EC_{tot} = measured streamflow EC ($\mu\text{S}/\text{cm}$); EC_{sf} = EC surface component ($\mu\text{S}/\text{cm}$) and
 176 EC_{bf} = EC baseflow component ($\mu\text{S}/\text{cm}$).

177 According to [Stewart et al. \(2007\)](#) and [Li et al. \(2014\)](#), an adequately long term monitoring activity
 178 ensures a full range of EC_{bf} and EC_{sf} variability to be explored. In this case EC_{bf} could be assumed as the
 179 end-member of the stream water conductivity during the period with the lowest streamflow, around 350
 180 $\mu\text{S}/\text{cm}$, while EC_{sf} as the end-member of the stream water conductivity during the highest streamflow
 181 period, around 80 $\mu\text{S}/\text{cm}$. These values, according to [Atekwana et al \(2004\)](#), are considered proxy values
 182 of TDS values of 170 and 40 mg/l obtained from the Ciciriello catchment hydro-chemical data analysis.
 183 The consequent hydrograph separation is illustrated in [Figure 3](#).

184 Considered as the ratio between the baseflow volume and the total streamflow volume, the Ciciriello
 185 watershed BaseFlow Index (BFI) is about 42%, consistent with the hydrogeological features of the
 186 catchment. Considering the climate characteristic of the studied area and the hydrogeological catchment
 187 properties, which emphasize the inter-annual hydrological response variability, it is important to note that
 188 both the total and baseflow discharge regimes are markedly seasonal ([Figure 4](#)). A low flow season exists,
 189 from June to November, when permanent bedrock springs sustain the streamflow and the baseflow
 190 component represents about 90% of total streamflow. A high flow period, from December to May, is
 191 counter posed, when baseflow represent only the 40% of total streamflow. In the following, it will be

192 showed that, accounting for this seasonal variability, is necessary to provide satisfactory performances in
193 the application of particular recursive digital filters.

194 3.2 Recession analysis

195 The application of digital hydrograph filtering techniques requires, as in the following explanation, an
196 analysis of the hydrograph recession process and an assessment of the recession constant, to be used as
197 filter parameter.

198 The recession curve is the lower part of the falling limb of a hydrograph and expresses the relation
199 between flow and time at low hydraulic heads. For purpose of hydrograph filtering, concern is pointed on
200 the baseflow recession, as the streamflow recession during periods of no direct runoff (Chapman, 1999).
201 Several curves have been suggested to represent the baseflow recession. The most used equation is the
202 simple exponential relationship (Maillet, 1905):

$$203 \quad Q_t = Q_0 e^{-\alpha t} = Q_0 k^t \quad (2)$$

204 where Q_t is the discharge at time t , Q_0 is the initial discharge and $k = e^{-\alpha t}$ is the recession constant and α is
205 the recession rate. In particular environment, such as the karstic regions, the hydrograph recession limb
206 can be furthermore featured by a decreasing or increasing recession rate during the depleting phase
207 (Fiorillo, 2011).

208 A streamflow hydrograph recession analysis has been performed for about 30 events, where differences
209 have been made between low flow and high flow periods. The analysed recession limbs (for the 30
210 events) have been extracted according to the following explanation. Hydrograph has been plotted on a
211 semi-logarithmic scale and the recession curve has been identified when observed data were aligned
212 along a straight line, assuming the linear reservoir concept would hold. During the recession phase two
213 different segments are clearly identified, regardless for the seasons and the event. For clarification, an
214 example, for two different low and high flow events, is illustrated in Figure 5. The largest recession rate
215 (α_1) would represent the quicker drainage from the shallow aquifers, occurring after intense recharge
216 during high water table conditions, whereas the smallest recession rate (α_2) would represent the slower
217 draining from the deep aquifer occurring during low water table level condition, typically during the dry
218 period (Fiorillo, 2011). The break between the two slopes is found by maximizing the goodness-of-fit for
219 the total duration of the recession limb. For each of the components a minimum number of 4 days of
220 observation has been considered to fit the linear reservoir equation. The α_2 is lower than α_1 regardless to

221 the event and to the season, with the lowest values for α_2 approached during the low flow season.
222 Average value for the recession rates and recession constants are provided in [Table 1](#) on a seasonal base.
223 The rate α_2 would represent a reliable estimation of the recession rate of interest for baseflow separation.
224 The objective identification of the baseflow, provided by the mass balance equation using electrical
225 conductivity data, allows the recession analysis to be performed for baseflow as well as for total flow,
226 providing a more appropriate estimation for the baseflow recession constant. The baseflow recession
227 process has been investigated for the same events selected for total streamflow recession analysis, and
228 results have been illustrated both in [Figure 5](#) and [Table 1](#). As well as for total flow, two different
229 segments are evident on the logarithmic plot, the slopes of which, although following the same rule ($\alpha_1 >$
230 α_2), are lower than total streamflow slopes. The most interesting consequence is the fact that very similar
231 values have been found for α_2 for both total and baseflow recessions, regardless for the season. For the
232 purpose of baseflow separation, this circumstance make reliable the use of the information derived from
233 the observed total streamflow, with interesting consequences for ungauged catchments, where tracer data
234 are not available.
235 Differences would have been significant for the case of an event scale analysis, where, compared to the
236 daily scale herein analysed, more than two different mechanism of runoff production must be accounted
237 for, as proposed in [Cuomo and Guida \(2016, under revision\)](#). In the following the comparison between an
238 uncalibrated and a calibrated application of recursive digital filters will illustrates the practical
239 implication.

240

241 **4. Digital empirical hydrograph filtering**

242 As previously mentioned, several approaches are reported in the scientific literature providing hydrograph
243 filtering methods for baseflow identification purposes. Two different methods, belonging to the recursive
244 digital filter group, have been applied for the Ciciriello experimental catchment data. These are the one
245 parameter algorithm ([Lyne and Hollick, 1979](#); [Chapman, 1991](#); [Chapman, 1999](#)) and the Eckhardt's two
246 parameters algorithm ([Eckhardt, 2005](#)). They have been applied as low-pass filters, providing the
247 separation of the total streamflow signal, y , into the high frequency component f (runoff) and the low
248 frequency component b (baseflow):

$$249 \quad y_t = f_t + b_t \quad (3)$$

250 where t is the time index. Lyne and Hollick (1979) proposed the filter equation:

$$251 \quad b_t = ab_{t-1} + \frac{1-a}{2}(y_t + y_{t-1}) \quad (4)$$

252 subject to the condition $b_t \leq y_t$, where a is the filter parameter. Chapman (1991) pointed out that the Lyne
 253 and Hollick algorithm incorrectly provides a constant baseflow b when direct runoff has ceased ($f = 0$),
 254 and therefore developed a new algorithm where the baseflow is a simple weighted average of the direct
 255 runoff and the baseflow at the previous time:

$$256 \quad b_t = ab_{t-1} + (1-a)f_t \quad (5)$$

257 which can be transformed in the following equation:

$$258 \quad b_t = \frac{a}{2-a}b_{t-1} + \frac{1-a}{2-a}y_t \quad (6)$$

259 when f is considered to be the difference between total and baseflow. Equation (6) is subject to the
 260 condition $b_t \leq y_t$, and a is the filter parameter that is the recession constant during period of no direct
 261 runoff (Chapman and Maxwell, 1996).

262 The Eckhardt filter algorithm has been demonstrated to be a flexible method and actually a number of
 263 one-parameter filters reported in the specific literature, are all special cases of the two-parameters
 264 Eckhardt's filter (Eckhardt, 2005). The baseflow component can be considered as:

$$265 \quad b_t = Ab_{t-1} + By_t \quad (7)$$

266 subject to the restriction $b_t \leq y_t$. Assuming a linear relation between outflow from the aquifer and its
 267 storage, parameters A and B in Equation (7) can be expressed as functions of the recession constant a , and
 268 second parameter, called the BFI_{max} , the maximum BFI value the algorithm is able to model. The
 269 following expressions indeed hold:

$$270 \quad \begin{cases} B = \frac{(1-a) \cdot BFI_{max}}{1-a \cdot BFI_{max}} \\ A = \left(\frac{1-BFI_{max}}{1-a \cdot BFI_{max}} \right) a \end{cases} \quad (8)$$

271 and the filter is then expressed as:

$$272 \quad b_t = \frac{(1-BFI_{max})ab_{t-1} + (1-a)BFI_{max}y_t}{1-aBFI_{max}} \quad (9)$$

273 subject to the restriction $b_t \leq y_t$. While the parameter a can be estimated by a recession analysis, there is
 274 no objective way to define BFI_{max} , for which the filter's author introduced pre-defined parameter

275 depending on geological and hydrogeological catchment properties. The author also suggested that these
276 pre-defined values can cause tendentious approximations in the BFI calculation, and that the coupled use
277 of different methods, such as tracer experiment, could be useful to optimize the parameter settings
278 (Eckhardt, 2005).

279

280 **5. Comparison between mass balance and digital filtering methods**

281 Empirical approaches, and among these digital filters, have found considerable success and have gained a
282 large popularity because of the possibility of application to many different hydro-geological and climate
283 environments. They can be applied using pre-defined filter parameters but to achieve an adequate
284 characterization of the baseflow component, a calibration phase is needed. The mentioned one parameter
285 and two parameters filters have been applied for the Ciciriello catchment, both in uncalibrated and a
286 calibrated procedures. For uncalibrated procedures, an application where filter parameters are set on pre-
287 defined values (based on catchment properties) is intended. For calibrated procedures, an application
288 where filter parameters, starting from pre-defined values, are tuned to reach a given result, is instead
289 intended. MBF (baseflow separated through the application of the MBF filter) baseflow indices and
290 statistics have been used for purpose of comparison and to proceed to the calibration phase. A statistical
291 analysis is performed to compare uncalibrated and calibrated approaches.

292 5.1 Uncalibrated digital filters application

293 The application of the one parameter filter only requires the identification of the baseflow recession
294 constant a (Eq. (6)). Results of the recession analysis previously reported have been used to this aim. If an
295 uncalibrated application is under investigation, recession constant can of course only be assessed for total
296 streamflow data. Table 1 results indicate that, at least for the studied catchment, the recession constant
297 exhibits a seasonal variability (on average 0.96 during the low flow season and 0.86 during the high flow
298 season). The recession analysis performed for the MBF baseflow series indicates that the same is not for
299 the baseflow recession constant (on average 0.94 during the low flow season and 0.91 during the high
300 flow season). The baseflow recession analysis further indicates that, on average, the total streamflow and
301 the baseflow recession constant during the low flow season are comparable (respectively 0.96 and 0.94).
302 In summary, for uncalibrated application to seasonal hydro-climate regimes catchments, the one
303 parameter filter a could then be realistically assumed as the total streamflow recession constant during the

304 low flow period. For the Ciciriello watershed, a ($= \alpha_2$) has been set to 0.96. This last value is also
305 comparable to the upper extreme of the range of values (0.90-0.95) proposed by [Nathan and McMahon](#)
306 [\(1990\)](#).

307 On the operational procedure, the one parameter filter has to be applied in a recursive algorithm. Rather
308 frequently, the filter is used with three passes over the data (forward, backward and forward again), to
309 smooth the baseflow series and to minimize the distortion effected produced by the filter itself ([Nathan](#)
310 [and McMahon, 1990](#); [Li et al., 2014](#)). [Spongberg \(2000\)](#) suggested that large values for the filter
311 parameter have to be compensated by a small number of passes, as the high frequency is completely
312 attenuated at the first step and further steps would only smooth the baseflow. [Spongberg \(2000\)](#) also
313 suggested that an even number of passes would minimize the signal phase distortion. According to such
314 indications and provided the large value (0.96) for the filter parameter, a number of two passes has been
315 used for the case study.

316 The application of the two parameters filter requires an assessment for the parameter a , the recession
317 constant, and for BFI_{max} . For the recession constant a , the discussion provided for the application of the
318 one parameter filter will hold. Thus also in this case it is assumed $a = \alpha_2$. For the BFI_{max} , a pre-defined
319 parameter, depending on geological and hydrogeological catchment properties, can be set. The Ciciriello
320 watershed belongs to the class of perennial streams with hard rock aquifers, for which pre-defined BFI_{max}
321 is equal to 0.25.

322 Baseflow index and baseflow statistics are illustrated in [Table 2](#) along with the percentage errors
323 computed with reference to the MBF baseflow statistics. Results are also illustrated in [Figure 6 \(left](#)
324 [panel\)](#) in terms of flow duration curves.

325 5.2 Digital filters calibration

326 Despite the very good performances, a calibrated version of the one parameter filter has been also
327 provided. The calibration has been obtained comparing the results of the MBF separation with the digital
328 filter application, minimizing the baseflow statistic percentage errors. The results of the calibration is $a =$
329 0.957, very similar to the parameter used in the uncalibrated application (0.96). Baseflow statistics and
330 percentage errors are reported respectively in [Table 3](#) and [Table 4](#).

331 In order to calibrate the two parameters algorithm, provided the stability of the recession constant as
332 illustrated in the calibration of the one parameter filter but also for purpose of application to ungauged

333 catchments where tracer data are not available, focus has been only set on the BFI_{max} parameter. Also in
334 this case, the calibration has been obtained comparing the results of the MBF separation with the digital
335 filter application, minimizing the baseflow statistic percentage errors. Assigned $a = 0.96$, the result of the
336 calibration is a $BFI_{max} = 0.47$, which is rather different compared to the uncalibrated case ($BFI_{max} = 0.25$).
337 Scientific statements about the error associated to an incorrect choice for the BFI_{max} value are indeed so
338 far contradictory, as in many studies confirmation or rejection of the pre-defined BFI_{max} have been
339 reported, without an evident and reliable explanation (Gonzales et al., 2009; Collishonn et al., 2013;
340 Cartwright et al., 2014; Stewart, 2015). Baseflow statistics and percentage errors are reported respectively
341 in Table 3 and Table 4.

342 EC data are undoubtedly valuable for the optimization of the parameter settings and minimization of
343 prediction errors but they can be further exploited to set a calibration procedure that is best suited to the
344 characteristics of the hydrological system under investigation.

345 The Ciciriello experimental catchment is a rainfall dominated hydrological system, for which distinct low
346 and high flow periods can be identified within the hydrological regime. Seasonality is embedded in the
347 climate and hydrological regime, but it is also hidden in the runoff generation, as indicated by the EC
348 measurements. Figure 7 (left side) illustrates the average daily observed electrical conductivity pattern for
349 a year-long time window. The blue dots indicate the observed EC for each of the Day Of the Year (DOY)
350 and the constant red line represent their average value. It is evident how for about one half of the year
351 (DOY 0 – 150) the EC is highly variable and below the average value, whereas for the second half (DOY
352 150 – 300), corresponding to the low flow period, it is rather stationary and consistently above the
353 average value. Assuming the EC as a proxy of the water sources contributing to runoff, it appears that
354 they are significantly different during the year, that in different seasons the system hydrological response
355 is different and that such differences need to be accounted for in a conceptual descriptive scheme.

356 The MBF technique intrinsically represent such seasonal variability as the actual baseflow value at a
357 particular day is constrained by the EC observed value at that day. Contrarily, the digital filters technique
358 assumes the hydrological system to behave similarly for each period of the year as the filter parameters
359 are unequivocally defined for the full time series. Evidently, the latter assumption poses a problem in the
360 descriptive capability of a strongly seasonal system, where the runoff generation mechanism switch from
361 one period to another.

362 To overcome the limit of the two parameters filter approach, a seasonal calibration of the same has been
 363 proposed. The optimization has been focused, also in this case, on the assessment of the optimal BFI_{max}
 364 value. Supported by the empirical evidence illustrated in [Figure 4](#) that hold for the Ciciriello catchments,
 365 only two seasons, a low flow and an high flow season, have been considered and for each of them a
 366 BFI_{max} has been calibrated. Values for the recession parameters a are taken from the results of the total
 367 streamflow recession analysis ([Table 2](#)).

368 The patterns illustrated in [Figure 7 \(left side\)](#) delineate the period of the year when runoff production
 369 switches from one to another dominant water generation sources. June to November appears to be the
 370 season where runoff is almost entirely produced by groundwater resources and for which it has been
 371 found an optimal value of $BFI_{max,low} = 0.77$ ($a_{low} = 0.96$). December to May is instead the season of the
 372 year dominated by the rainfall contribution to total discharge and for which it has been found an optimal
 373 value of $BFI_{max,high} = 0.38$ ($a_{high} = 0.86$). Results have been illustrated in [Table 3](#) and [Table 4](#), as statistics
 374 assessments and percentage of relative errors, and in [Figure 7 \(right side\)](#) as flow duration curves.

375 5.3 Statistical analysis

376 In terms of uncalibrated procedures, it is clearly evident that the one parameter filter outperforms the
 377 more flexible two parameters algorithm. Percentage errors for global BFI index are about 2% for the first
 378 case and about 35% for the second case. The average baseflow process is also well described by the one
 379 parameter filter. Largest errors are detected for the maximum baseflow value, but this condition is
 380 common to both procedures. Flow duration curves are compared by the AAPE index estimated (for each
 381 of the applied methods) as in the following ([Longobardi and Villani, 2013](#)):

$$382 \quad AAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Q_{MBF,i} - Q_{FIL,i}}{Q_{MBF,i}} \right| \quad (10)$$

383 where i is the decile order, $Q_{MBF,i}$ is the MBF baseflow value corresponding to the i -th decile, $Q_{FIL,i}$ is the
 384 baseflow resulted from the different filter algorithms value corresponding to the i -th decile, n the
 385 considered deciles.

386 Compared to the MBF baseflow, the uncalibrated one parameter baseflow duration curve also presents
 387 almost an optimal fitting with an average AAPE of 20% ([Table 5](#)). The uncalibrated two parameters
 388 baseflow duration curve describes instead a significant underestimation of the baseflow for almost all of
 389 the durations with an average error of about 40% ([Table 5](#)).

390 With reference to the calibrated procedures, statistical performances for the calibrated one parameter filter
391 are almost identical to the uncalibrated case. An improvement, compared to the uncalibrated case, is
392 instead evident for the two parameters filter (Table 2 and Table 4) but large errors of about 28% are still
393 found in the (under) prediction of baseflow minimum value. The maximum value is also over predicted,
394 such as in the case of the one parameter filter, of about 12%. The AAPE index also results in an
395 improvement moving from 40% to 19% (Figure 7 and Table 5). The seasonal calibration further improves
396 the performance of the baseflow separation filter, especially for what concerns the underestimation of
397 minimum baseflow values, which moves from about 28% for the traditional calibration to about 9%. The
398 AAPE index results in a further improvement moving from 49% to 16% (Figure 7 and Table 5).

399 Beyond the comparison between main descriptive statistics, the empirical baseflow distribution for the
400 MBF and the different applied filters are compared. The box plot in Figure 8 and the quantile-quantile
401 plots in Figure 9 illustrates some of the distribution properties. In agreement with the MBF baseflow
402 distribution, all of the analysed filters, both uncalibrated and calibrated, generate asymmetric
403 distributions, for which the larger discrepancies occur for the larger order percentiles assessment,
404 maximum values and outliers consistency. Besides the main descriptive statistics already introduced, the
405 one parameter filter for the uncalibrated and calibrated cases distributions are also equivalent and very
406 close to the MBF distribution until the 90% percentile. Indeed the AAPE index is about 10%, half of the
407 index value corresponding to the 100% percentile (Table 5 and Figure 9). The calibration and more
408 evidently the seasonal calibration for the two parameters filter also results in an improvement in the
409 empirical distribution compared to the MBF. The calibrated two parameters filter distribution adapts to
410 the MBF distribution with an AAPE error of about 10% until the 80% percentile (Table 5 and Figure 9)
411 but significantly differs for larger percentiles order (AAPE = 19% for 100% percentile). The seasonal
412 calibrated two parameters filter represents the outperforming method: the outlier consistency is similar to
413 the MBF distribution and, as the one parameter filter, it adapts the MBF distribution until the 90%
414 percentile with smaller errors for larger percentile orders (Table 5 and Figure 9).

415

416 **6. Discussion and conclusion**

417 The paper has presented an analysis of the ability of digital hydrograph filtering tools for the
418 characterization of the baseflow source contributing to total streamflow for a typical, small, sandstone,

419 rainfall-dominated catchment. Electrical conductivity monitoring data and the related objective mass
420 balance hydrograph separation, have provided useful indication about the selection, application and
421 calibration for digital filters for seasonal flow regimes and have moreover provided, for these particular
422 cases, practical indication for baseflow separation for catchments where tracer data are not available.

423 One of the main result deals indeed with the one parameter filter, only based on the assessment of the
424 recession constant, which appear to be the most efficient in the description of the baseflow pattern and
425 empirical distribution. The larger flexibility, embedded at least within the conceptual description by the
426 two parameters filter, appears instead as a complexity for a strongly seasonal hydrological system, such as
427 the studied catchment. It would indeed require a larger number of parameters to be calibrated, two for
428 each of the identified seasons, in order to get reliable baseflow pattern description and empirical
429 distribution, especially for what concerns the low flow season assessment.

430 Concerning the application of baseflow digital filtering techniques to watersheds where tracer data are not
431 available, and at least for the class of catchments to which the investigated system belongs, the presented
432 paper has pointed out the feasibility for a reliable recession constant to be derived by the total streamflow
433 analysis, performing an accurate calibration of recession events during the low flow season, which has
434 appeared to be the most critical for the investigated basin.

435 During the high flow period, the one and the two parameters filters are respectively associated to an
436 overestimation (20%) and underestimation (10%). For this period of the year, the monitoring campaign
437 strongly indicates a large range of variability for the EC values, probably caused by not only dilution and
438 mixing, but also by dispersion processes from different water sources and flow paths (Cuomo and Guida
439 2016, under revision). The variability is intrinsically embedded within the MBF method but it is not at all
440 accounted for by the digital filters, which are only able to distinguish between two different component
441 and between two main dominating runoff production mechanisms. The one parameter filter, basically
442 calibrated on the low flow season, in fact produces good estimates of the minimum value of baseflow (5%
443 error) while considerable overestimation (20%) is found for the highest values, typically occurring during
444 the high flow season. The two parameters filter, seasonally calibrated, produces errors comparable to the
445 one parameter filter for what concerns the minimum (10%) but it is able to enhance also the description of
446 the maximum values, with a reduction of the error (in underestimation) of 10%. The relative outlier

447 consistency is similar to the MBF distribution and it adapts the MBF distribution until the 90% percentile
448 with smaller errors for larger percentile orders.

449 Digital filters, at least for the case study and for similar conditions, appear then sufficiently adequate to
450 estimate time averages baseflow at annual scale from daily streamflow data. At the same time, they are
451 not suitable for a more realistic representation of the baseflow pattern and its seasonal variability. More
452 articulate conceptualization of the hydrological behaviour of the catchment, including different runoff
453 generation mechanisms and a high-frequency data recording would be needed for an improvement, taking
454 groundwater ridging, excess saturation and soil pipe runoff into account ([Longobardi et al. 2014](#); [Cuomo
455 and Guida 2016, under revision](#)).

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589 New Brunswick Canada, using a recursive digital filter calibrated with the conductivity mass
590 balance method. *Hydrol. Process.* , 27, 2659–2665.
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592 **Figure captions**

593

594 Figure 1: Hydrogeological scheme of the Cilento UNESCO Global Geopark (Aloia et al., 2013). The
595 experimental studied catchment location is indicated by a yellow box in the south eastern area
596 of the Cilento Global Geopark.

597

598 Figure 2: Schematic geological map and monitoring stations of the Ciciriello experimental catchment
599 (Cilento UNESCO Global Geopark).

600

601 Figure 3: Discharge, MBF baseflow separation and electrical conductivity measurements at the T.
602 Ciciriello watershed main station.

603

604 Figure 4: Figure 4. Mean monthly MBF baseflow contribution to total streamflow at T. Ciciriello
605 watershed main station.

606

607 Figure 5: Recession analysis during low flow period (left panel) and high flow period (right panel).

608

609 Figure 6: Left side. Electrical conductivity mass balance filtering (MBF) and recursive digital filters (one
610 and two parameters) baseflow duration curves. Right side. Calibrated two parameters filter
611 baseflow underestimation during low flow period.

612

613 Figure 7. Left side. Electrical conductivity annual pattern. Right side. MBF, calibrated and seasonally
614 calibrated two parameters baseflow duration curves.

615

616 Figure 8. Box plot for mass balance, uncalibrated and calibrated one and two parameters filters
617 application.

618

619 Figure 9. Quantile-quantile plot for mass balance versus uncalibrated and calibrated one and two
620 parameters filters application.

621 **Table captions**

622

623 Table 1: Seasonal assessment for the smallest component of the recession rate (α_2) and related recession
624 constant (k_2) for both total and baseflow.

625

626 Table 2: Baseflow statistics for MBF, uncalibrated one and two parameters filters. Errors refer to MBF
627 baseflow separation.

628

629 Table 3: Baseflow statistics for MBF, calibrated one and two parameters filters.

630

631 Table 4: Percentage errors (comparison with MBF baseflow) for calibrated one and two parameters
632 filters.

633

634 Table 5. AAPE index (%) for uncalibrated and calibrated one and two parameters filters.

Table 1. Seasonal assessment for the smallest component of the recession rate (α_2) and related recession constant (k_2) for both total and baseflow.

	Low flow period		High flow period	
	α_2	k_2	α_2	k_2
totalflow	0.04	0.96	0.15	0.86
baseflow	0.06	0.94	0.16	0.91

Table 2. Baseflow statistics for MBF, uncalibrated one and two parameters filters. Errors refer to MBF baseflow separation

	MBF	One parameter ($a = 0.96$)	Two parameters ($a = 0.96$; $BFI_{max} = 0.25$)	One parameter (% error)	Two parameters (% error)
BFI	0.42	0.41	0.27	2.38	35.71
Min (l/s)	1.75	1.67	0.68	4.57	61.14
Mean (l/s)	34.25	33.70	22.13	1.61	35.39
Max (l/s)	262.01	200.06	111.81	23.64	57.33
Std (l/s)	45.18	44.90	25.47	0.62	43.63

Table 3. Baseflow statistics for MBF, calibrated one and two parameters filters.

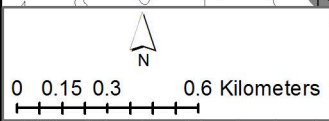
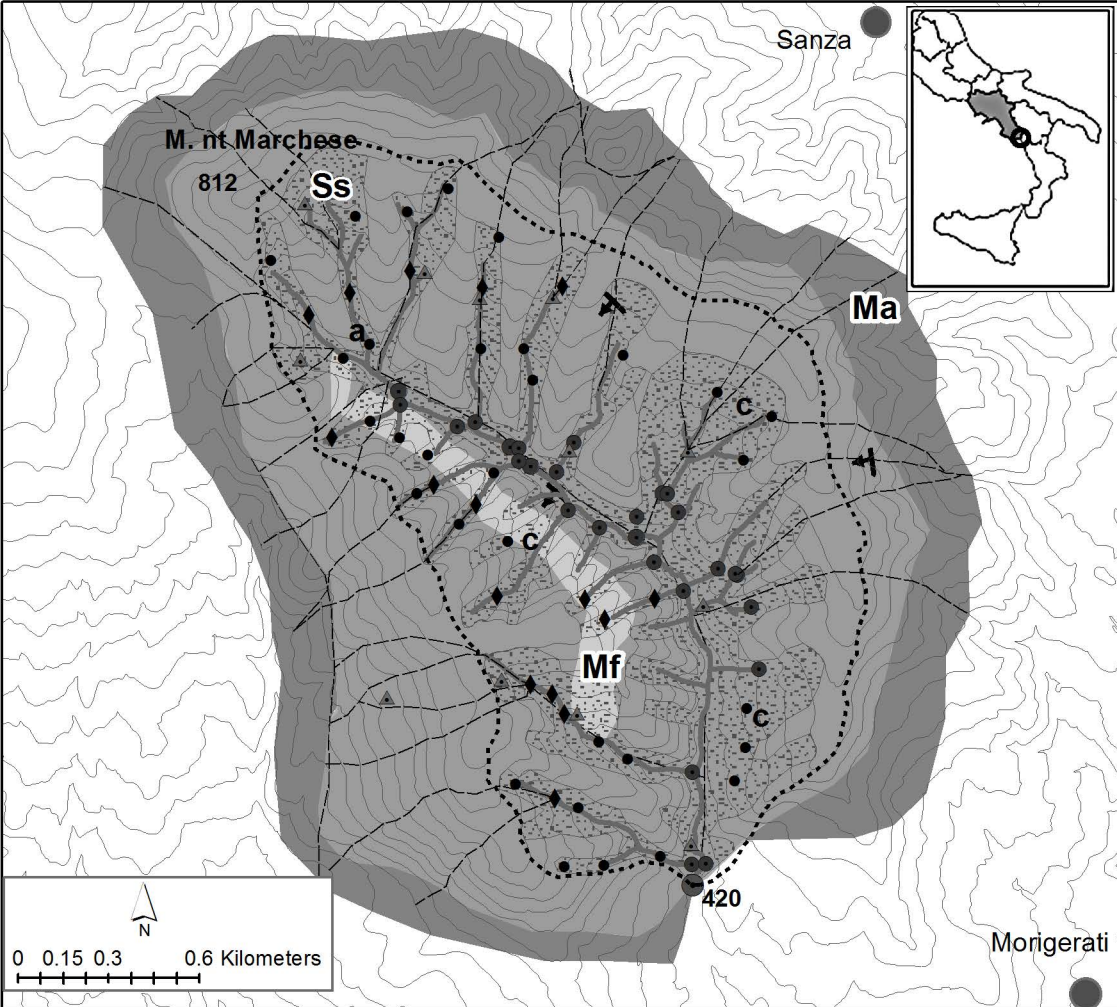
	One parameter ($a = 0.957$)	Two parameters ($a = 0.96$; $BFI_{max} = 0.47$)	Two parameters ($a_{low} = 0.96$; $BFI_{max,low} = 0.77$) ($a_{high} = 0.86$; $BFI_{max,high} = 0.38$)
BFI	0.42	0.42	0.42
Min (l/s)	1.67	1.26	1.41
Mean (l/s)	34.22	34.60	34.32
Max (l/s)	207.86	230.17	290.13
Std (l/s)	45.95	45.98	49.09

Table 4. Percentage errors (comparison with MBF baseflow) for calibrated one and two parameters filters.

	One parameter ($a = 0.957$)	Two parameters ($a = 0.96$; $BFI_{max} = 0.47$)	Two parameters ($a_{low} = 0.96$; $BFI_{max,low} = 0.77$) ($a_{high} = 0.86$; $BFI_{max,high} = 0.38$)
BFI	0.00	0.00	0.00
Min (l/s)	4.57	28.00	9.20
Mean (l/s)	0.09	-1.02	-0.20
Max (l/s)	20.67	12.15	-10.73
Std (l/s)	-1.70	-1.77	-8.65

Table 5. AAPE index (%) for uncalibrated and calibrated one and two parameters filters.

decile	One param. uncalibrated	Two param. uncalibrated	One param. calibrated	Two param. calibrated	Two seasonal calibrated
80%	9	28	10	12	12
90%	10	34	10	16	14
100%	19	40	19	19	16



Bedrock

- Mf** Marly
- Ss** Sandstone
- Ma** Marly-clayey

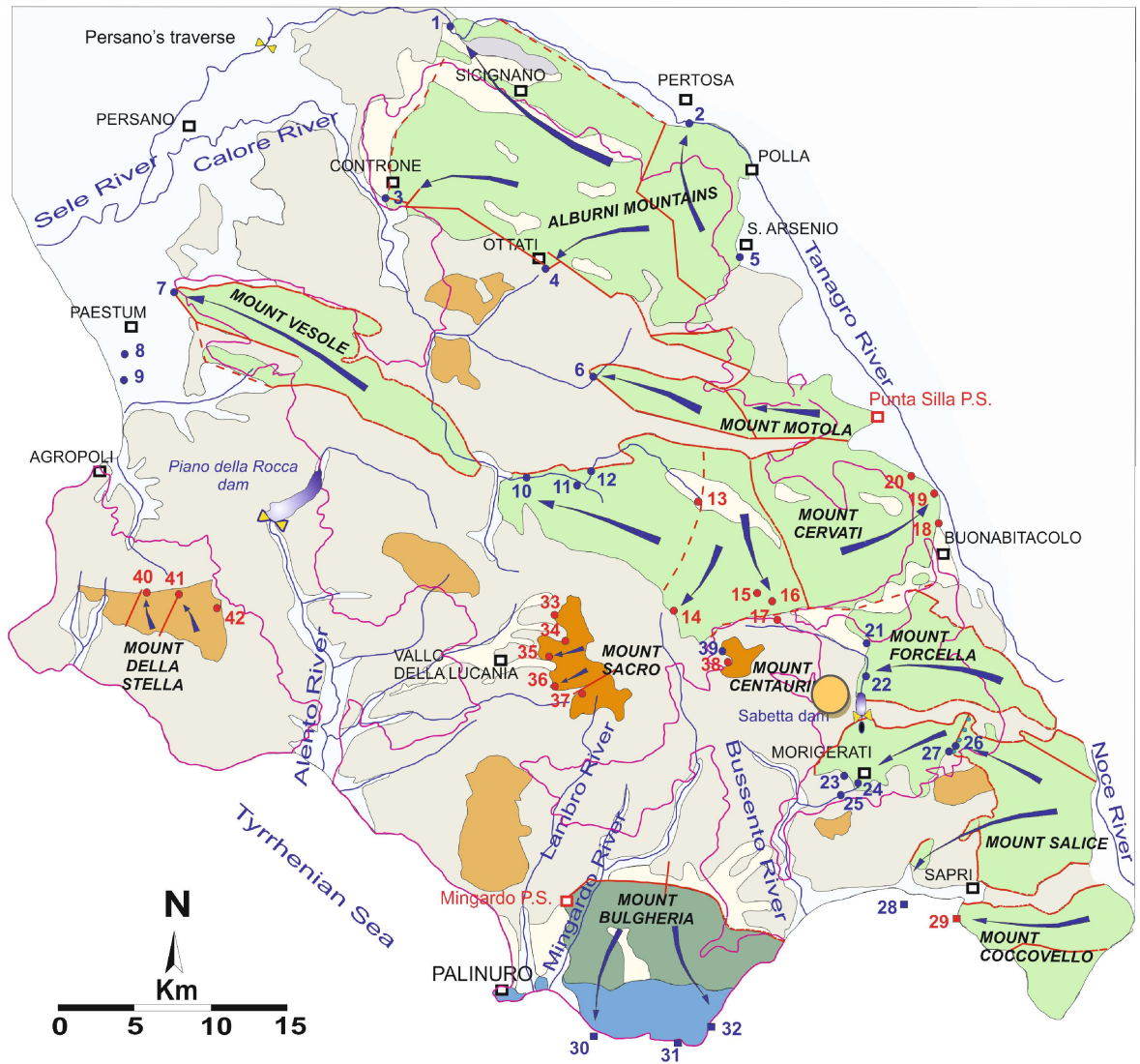
Soil

- c** Colluvial
- a** Alluvial


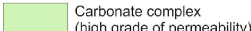
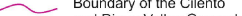





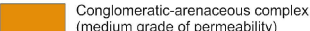
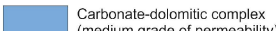


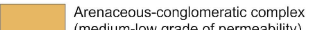



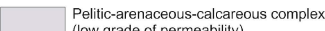

Monitoring system

- Main station
- Sub station
- Secondary station
- ▲** Spring station
- Rain gauge
- Control point
- ◆** Zob_riparian corridor station (weir/ piezometer)

- Fault
- ▲ Strata attitude



Legend

- | | | | | | | | |
|--|---|---|--|---|---|--|---|
|  | Alluvial complex |  | Carbonate complex (high grade of permeability) |  | Boundary of the Cilento and Diano Valley Geopark |  | Directions of groundwater flow |
|  | Detrital complex |  | Carbonate-detrital complex (high-medium grade of permeability) |  | Main tectonic features of hydrogeological relevance |  | Karst sinkhole |
|  | Conglomeratic-arenaceous complex (medium grade of permeability) |  | Carbonate-dolomitic complex (medium grade of permeability) |  | Principal subaerial springs, untapped and tapped respectively |  | Dams (Piano della Rocca e Sabetta) |
|  | Arenaceous-conglomeratic complex (medium-low grade of permeability) |  | Ciceriello Study area |  | | Principal pumping-well stations |  |
|  | Pelitic-arenaceous-calcareous complex (low grade of permeability) | | |  | Submarine springs, untapped and tapped respectively | | |

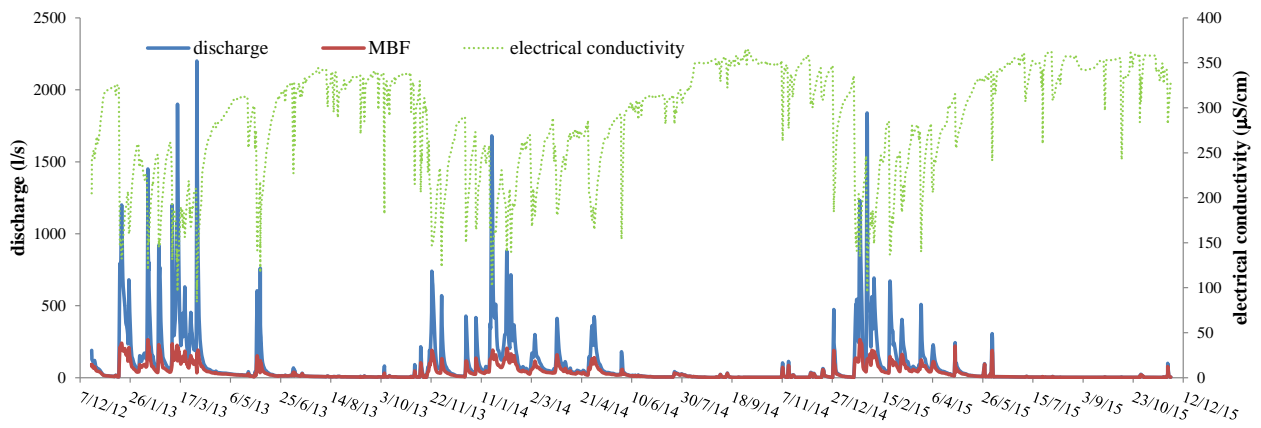


Figure 3. Discharge, MBF baseflow separation and electrical conductivity measurements at the T. Ciciriello watershed main station.

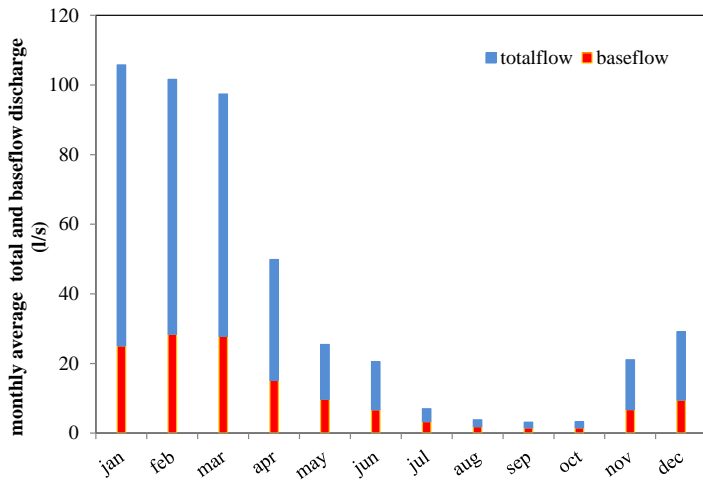


Figure 4. Mean monthly MBF baseflow contribution to total streamflow at T. Ciciriello watershed main station.

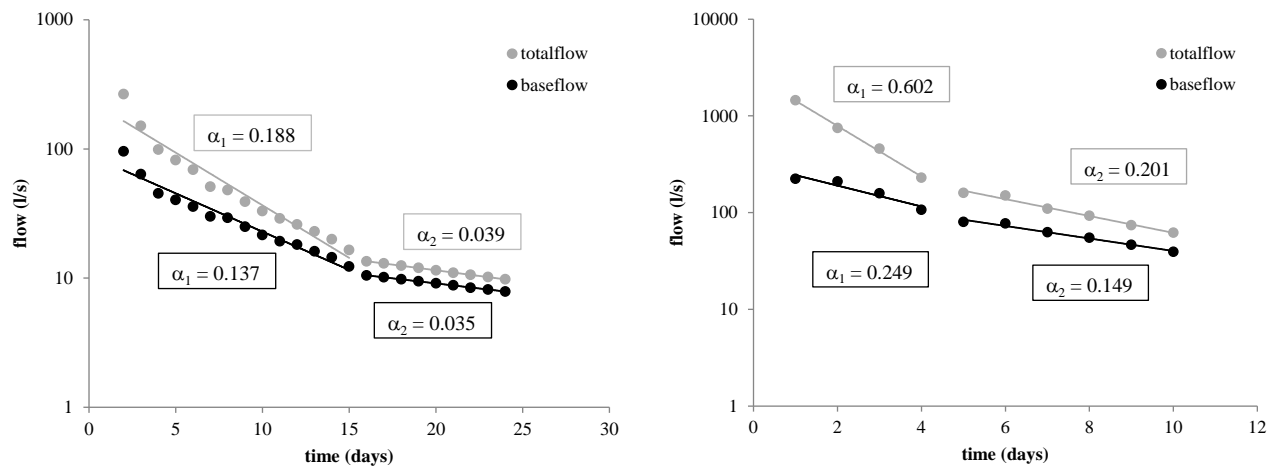


Figure 5. Recession analysis during low flow period (left panel) and high flow period (right panel).

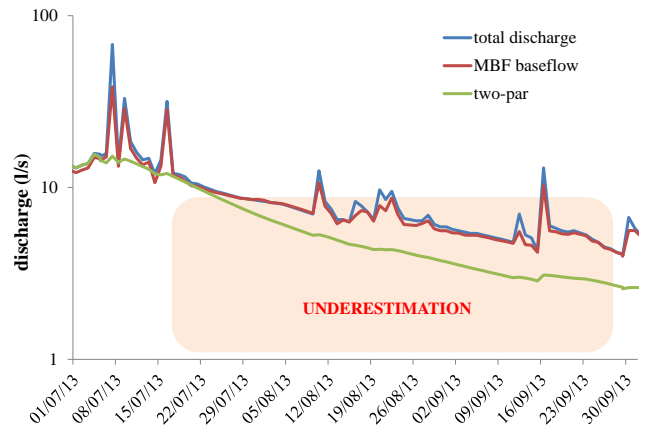
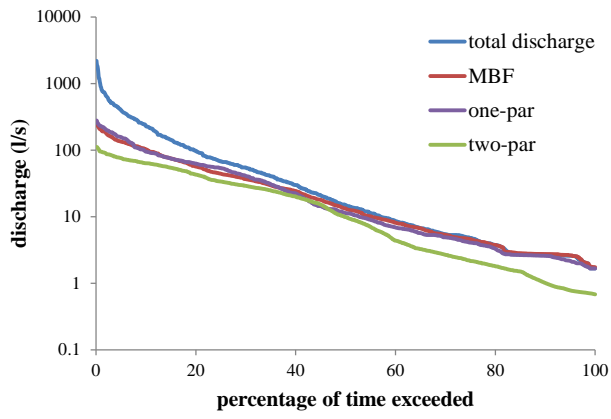


Figure 6. Left side. Baseflow duration curves for mass balance filtering (MBF), uncalibrated digital filters (one and two parameters). Right side. Calibrated two parameters filter baseflow underestimation during low flow period.

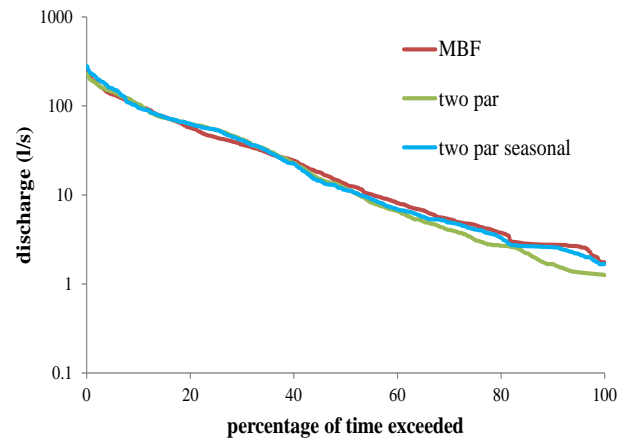
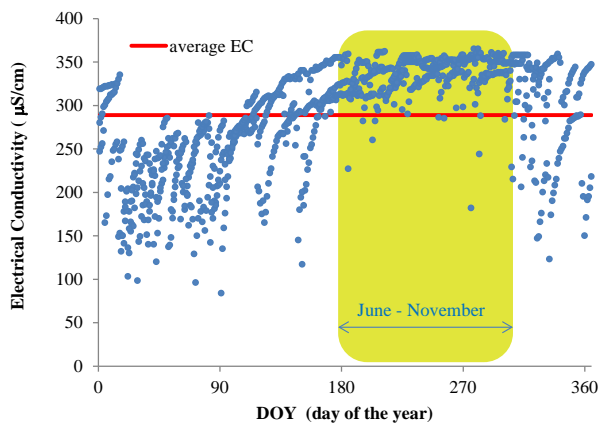


Figure 7. Left side. Electrical conductivity annual pattern. Right side. MBF, calibrated and seasonally calibrated two parameters baseflow duration curves.

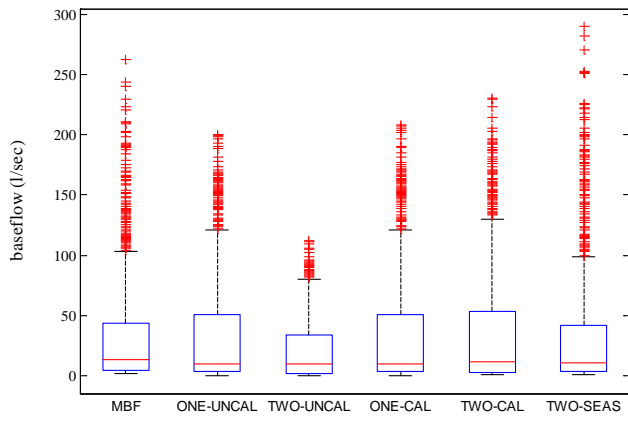


Figure 8. Box plot for mass balance, uncalibrated and calibrated one and two parameters filters application.

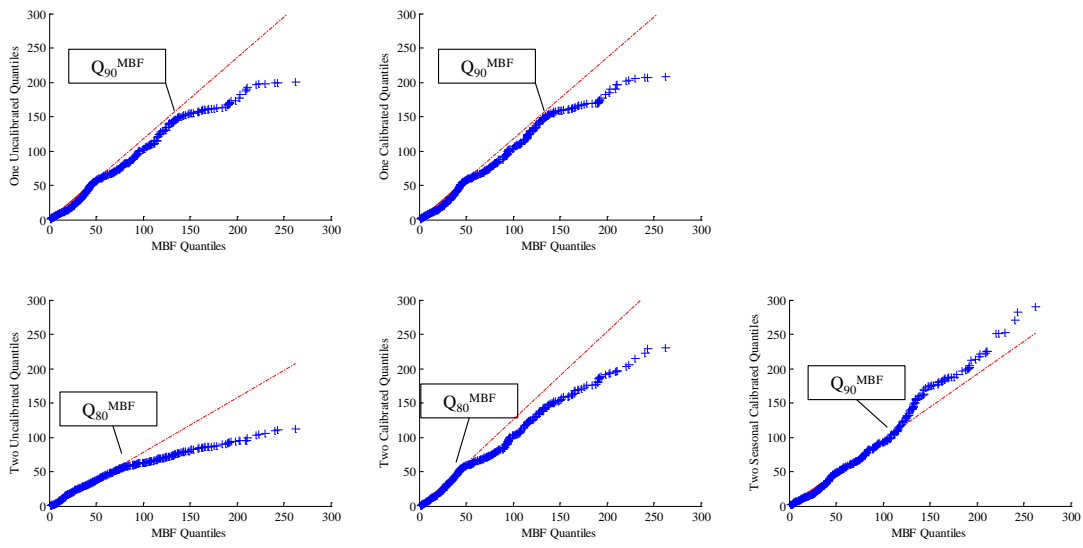


Figure 9. Quantile-quantile plot for mass balance versus uncalibrated and calibrated one and two parameters filters application.

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Std (l/s)	45.18	44.90	25.47	0.62	43.63

Table 3. Baseflow statistics for MBF, calibrated one and two parameters filters.

	One parameter (a = 0.957)	Two parameters (a = 0.96; BFI _{max} = 0.47)	Two parameters (a _{low} = 0.96; BFI _{max,low} = 0.77) (a _{high} = 0.86; BFI _{max,high} = 0.38)
BFI	0.42	0.42	0.42
Min (l/s)	1.67	1.26	1.41
Mean (l/s)	34.22	34.60	34.32
Max (l/s)	207.86	230.17	290.13
Std (l/s)	45.95	45.98	49.09

Table 4. Percentage errors (comparison with MBF baseflow) for calibrated one and two parameters filters.

	One parameter (a = 0.957)	Two parameters (a = 0.96; BFI _{max} = 0.47)	Two parameters (a _{low} = 0.96; BFI _{max,low} = 0.77) (a _{high} = 0.86; BFI _{max,high} = 0.38)
BFI	0.00	0.00	0.00
Min (l/s)	4.57	28.00	9.20
Mean (l/s)	0.09	-1.02	-0.20
Max (l/s)	20.67	12.15	-10.73
Std (l/s)	-1.70	-1.77	-8.65

Table 5. AAPE index (%) for uncalibrated and calibrated one and two parameters filters.

decile	One param. uncalibrated	Two param. uncalibrated	One param. calibrated	Two param. calibrated	Two seasonal calibrated
80%	9	28	10	12	12
90%	10	34	10	16	14
100%	19	40	19	19	16