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1 Urban hydrologic trend analysis based on rainfall and runoff data analysis and conceptual
2 model calibration

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11

12 **Keywords**

13 Urban hydrology; urbanization; conceptual rainfall-runoff model; trend analysis; Mann-
14 Kendall test

15 **Abstract**

16

17 Urban stormwater is a major cause of urban flooding and natural water pollution. It is
18 therefore important to assess any hydrologic trends in urban catchments for stormwater
19 management and planning. This study addresses urban hydrological trend analysis by
20 examining trends in variables that characterize hydrological processes. The original and
21 modified Mann-Kendall methods are applied to trend detection in two French catchments, i.e.,
22 Chassieu and La Lechere, based on approximately one decade of data from local monitoring
23 programs. In both catchments, no trend is found in the major hydrological process driver (i.e.,
24 rainfall variables), whereas increasing trends are detected in runoff flow rates. As a
25 consequence, the runoff coefficients tend to increase during the study period, probably due to
26 growing imperviousness with the local urbanization process. In addition, conceptual urban
27 rainfall-runoff model parameters, which are identified via model calibration with an event

28 based approach, are examined. Trend detection results indicate that there is no trend in the
29 time of concentration in Chassieu, whereas a decreasing trend is present in La Lechere, which,
30 however, needs to be validated with additional data. Sensitivity analysis indicates that the
31 original Mann-Kendall method is not sensitive to a few noisy values in the data series.

32 **1. Introduction**

33 Urban stormwater is a major cause of urban flooding and water pollution, which can lead to
34 serious economic and social consequences. Currently, it is widely recognized that effects that
35 are closely related to human activities, such as climate change and urbanization can result in
36 significant alteration of stormwater quantity and quality (e.g., Astarai-Imani et al., 2012).

37 The design and operation of urban storm water projects that aim to reduce the adverse impact
38 of stormwater should take possible changes in urban hydrology patterns into account. It is
39 therefore important to assess any hydrologic trend (if one exists) in urban catchments.

40 Considerable attention has been paid to trend analysis in research areas in climatology,
41 hydrology and water quality in recent years. Examples of trend detection applications in water
42 resources studies include trend studies of precipitation (e.g., Xu et al., 2003; Partal and Kahya,
43 2006; Gocic and Trajkovic, 2013), streamflow (e.g., Douglas et al., 2000; Zhang et al., 2001;
44 Burn and Elnur, 2002; Yue et al., 2002; Aziz and Burn, 2006), and river and drainage water
45 quality (Hirsch et al., 1982; Awadallah et al., 2011; Sun et al., 2015). A number of trend
46 detection methods including parametric and non-parametric tests have been applied (Hess et
47 al. 2001). A non-parametric test is generally more suitable for non-normally distributed and
48 censored data, which are frequently encountered in water resources data (Yue et al., 2002).

49 The Mann-Kendall method (Mann, 1945; Kendall, 1955) is one of the most commonly used
50 non-parametric trend detection tests (e.g., Omar et al., 2006). Because the Mann-Kendall
51 method generally requires serial independence, some previous studies have modified the

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52 Mann-Kendall Method to apply it to data presenting seasonality or serial correlations (e.g.,
53 Hirsch and Slack, 1984; Hamed and Rao, 1998; Yue et al., 2002).

54 A rainfall-runoff model that transforms the meteorological forcing (rainfall) into the
55 hydrological response of a catchment (runoff) is an important tool for theoretical and applied
56 research in hydrology. A simple conceptual rainfall-runoff model can sometimes serve as a
57 powerful tool for aiding in understanding local hydrological processes. For instance, the
58 hydrological response can be linked to landscape attributes by deriving the relationship
59 between hydrological model parameters and landscape attributes (e.g., Post and Jakeman,
60 1999). Statistically significant correlations between some parameters of a conceptual daily
61 rainfall-runoff model and the catchment physical and climatic characteristics were found
62 (Chiew et al., 2002). Hence, the interpretability of the rainfall-runoff model parameters can
63 possibly shed some light on the hydrologic behaviour of a catchment (Maneta et al., 2007).

64 Given the importance of assessing hydrologic trend in urban catchments, the main objective
65 of this paper is to present a methodology that identifies and quantifies hydrologic trend. The
66 hydrological trend analysis is addressed using a dual approach, i.e., by analysing both rainfall
67 and runoff data and model parameters identified from the calibration of a conceptual
68 hydrological model. The rationale of examining possible hydrological trends via calibrated
69 hydrological model parameters is that if there is any change in the local hydrologic process,
70 non-stationarity will probably be present in model parameters characterizing the temporal
71 hydrological process. In addition to direct analysis of rainfall and runoff data, a conceptual
72 urban hydrological model helps investigate more characteristics of local hydrology (e.g.,
73 initial precipitation losses and the time of concentration), which cannot be measured directly.
74 However, it should be noted that the evolution of hydrological processes is an aggregate result
75 of changes of many distributed factors and processes on smaller scales (than the catchment
76 scale) in local hydrology (e.g., changes in distributed land uses and hydrological properties),

77 using a conceptual rainfall-runoff model, this study only addresses the evolution of model
78 parameters that are highly lumped on the catchment scale which reveal the general
79 hydrological responses of urban/peri-urban catchments. The evolution of the hydrological
80 trend provides the most direct evidence of changes in local hydrology and the quantification
81 of the trends in relevant parameters is useful in urban stormwater management. The evolution
82 of processes, factors and properties on smaller scales than the catchment scale is beyond the
83 discussion of this study. This study also provides guidance for analysing long-term
84 hydrological trends by applying temporal calibration of a conceptual hydrological model. The
85 effectiveness of such an approach is demonstrated via applications of the methodology to two
86 French catchments.

87 **2. Case studies and data**

88 Two urban catchments in the suburbs of Lyon, France, i.e., the Chassieu catchment and the La
89 Lechere catchment, are studied in this paper. Both catchments are monitoring sites under the
90 OTHU program (www.othu.org), which has been operating for over a decade to improve our
91 knowledge on urban water system management by acquiring reliable data of both wet and dry
92 weather flows and their impacts on the receiving environment.

93 The Chassieu catchment is located in the east of the Greater Lyon area. It covers an industrial
94 area of 185 ha with an imperviousness coefficient of approximately 0.72. The catchment is
95 drained by a separate stormwater sewer system, which also receives dry weather flows from
96 cooling of industrial processes (that can be assumed clean). The pervious area is not
97 connected to the sewer system. Rainfall in Chassieu was measured by a tipping-bucket rain
98 gauge installed in the catchment, and a six-minute rainfall time series is available. The
99 catchment runoff flow rate was computed from water depth measurements in the 1.6 m
100 circular concrete pipe at the outlet of the catchment using the Manning equation (calibrated
101 and validated using measured water depth and velocity data in the pipe) with a two-minute

102 interval from 2004 to 2011. The rainfall and runoff time series suffer from 7.4% and 13.1%
103 missing data, respectively.

104 La Lechere catchment is located to the west of Lyon. The catchment covers a maximum area
105 of 410ha when all of the combined sewer overflows (CSOs) are activated. The land in the
106 catchment is mainly composed of urban areas (53%), agricultural fields (45%) and forests
107 (3%) (Braud et al., 2013). The urban areas are drained by combined sewer networks, with
108 several CSOs connected to the Chaudanne River. The contributing area of stormwater to the
109 combined sewer system is approximately 120 ha (stormwater from other areas are not
110 connected to the sewers). In addition to the CSOs, the Chaudanne River also receives natural
111 flows from rural areas. More details about the catchment can be found in Jankowfsky et al.
112 (2014). Rainfall was measured by a tipping-bucket rain gauge located in the catchment. A
113 one-minute rainfall time series is available with approximately 13.7% missing data. The
114 runoff flow in the Chaudanne River, mainly composed of CSOs from urban areas and natural
115 streamflow from rural areas, was computed from water depth measurements in the calibrated
116 Parshall flume at a gauge station. The runoff flow data are registered with varied time steps,
117 typically from two minutes to one hour. A two-minute time series was created using a linear
118 interpolation method. 2.8% of the runoff flow data is missing. Rainfall and flow data are both
119 available from June 2005 to December 2014.

120 **3. Methodology**

121 **3.1 Mann-Kendal test and modified Mann-Kendall test**

122 The Mann-Kendall method is a rank-based nonparametric trend detection test extensively
123 applied in climatology and hydrology. The null hypothesis of the Mann-Kendall test H_0 states
124 that the data are a sample of n independent and identically distributed random variables,
125 whereas the alternative hypothesis H_1 is that x_k and x_j are not from identical distributions (k, j
126 $\leq n$ and $k \neq j$). The test statistic S is defined as:

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$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (1)$$

127 where $\text{sgn}(\theta)$ is the sign function that equals -1, 0 and 1 when θ is below, equal to and above 0,
128 respectively. Under the null hypothesis, S is asymptotically normally distributed with the
129 mean of 0 and a constant variance, which is a function of the number of data in a tested data
130 series (e.g., Hess et al., 2001; Gocic and Trajkovic, 2013). A P -value, which presents the
131 probability of obtaining samples as extreme as the observed ones, can be computed from
132 given S and its variance. The null hypothesis is accepted with a higher P -value than a
133 predefined significance level. Otherwise, the null hypothesis is rejected, suggesting that a
134 trend is detected. Two levels of significance, i.e., 5% and 1%, are used in this study.

135 The Mann-Kendall method usually indicates a higher false positive outcome for data with
136 positive autocorrelation, and it is thus no more effective for auto-correlated time series (e.g.,
137 Yue et al., 2002). A modified Mann-Kendall trend test (Hamed and Rao, 1998) is used when
138 the autocorrelation effect in a data series is significant. In the modified Mann-Kendall method,
139 the variance of S is calculated using an empirical formula with a multiplicative coefficient,
140 which is a function of the autocorrelation coefficient (see Hamed and Rao, 1998 for the
141 formula). As a trend generally leads to positive autocorrelation, a data series is firstly
142 detrended with a linear trend estimated from linear regression. The detrended data series is
143 then tested for its autocorrelation effect (Yue et al., 2002). If the autocorrelation in a data
144 series is insignificant at the 5% significance level, the Mann-Kendall test is applied.
145 Otherwise, the modified Mann-Kendall test is performed.

146 The slope of a trend (if one exists) can be estimated by a non-parametric index (Sen, 1968)
147 based on the assumption of a linear trend:

$$\beta = \text{Median} \left((x_j - x_i) / (j - i) \right), \quad i < j \quad (2)$$

148 The value of β represents the changing value per event if an event-based data series is
149 considered. An annual slope of a trend is computed by multiplying the average number of
150 events in one year to this value.

151 **3.2 Rainfall and runoff event identification**

152 Storm events are identified from continuous rainfall time series with a dry period over four
153 hours between two events, which is empirically identified (Métadier and Bertrand-Krajewski,
154 2012; Sun et al., 2015). This study concerns only urban rapid flow. For most events, the rapid
155 response of runoff to rainfall from urban areas ends in four hours in both catchments
156 according to visual inspection. The time series of runoff is thus identified covering the period
157 of a corresponding rainfall and four hours more after the rainfall event ends. In La Lechere,
158 the measured runoff flows in the Chaudanne River are partly from upstream rural areas, which
159 respond much slower than urban areas. A baseflow, considered as a constant flow with the
160 flow rate equal to the minimum flow rate measured during an event, is subtracted from the
161 measured runoff time series to identify the urban rapid flow part. The baseflow in Chassieu
162 mainly comes from industrial wastewater. For most events, the assumption of a constant
163 baseflow during an event for several hours is reasonable.

164 Only significant events are considered for trend analysis of urban hydrological processes, as
165 parameters characterizing small events are easily affected by influential factors such as initial
166 rainfall loss, baseflow and measurement uncertainty. Significant events in Chassieu are
167 defined with a total rainfall depth over 1 mm and duration over 30 minutes. In La Lechere, a
168 higher threshold with 2 mm rainfall depth and over 30-minute duration is adopted because the
169 CSOs in the combined sewers are often not activated during smaller events. In addition, a
170 significant event in both catchments requires a mean urban runoff flow over 5 L/s.

171 **3.3 Simple parameters characterizing hydrological processes**

172 Two simple parameters that can be directly calculated from rainfall and runoff data without
173 modelling, i.e., the runoff coefficient and lag time, are derived for each event. The runoff
174 coefficient is the ratio of runoff water volume to rainfall volume, arbitrarily representing the
175 proportion of rainfall entering the drainage system, which is generally a function of land
176 covers and imperviousness of the area. Trend analysis of the runoff coefficient of rapid urban
177 runoff can possibly reveal the evolution in local urbanization. The lag time measures the
178 response time of a catchment to a rainfall event, which is closely related to the topography,
179 geology and land use within a catchment. In this study, the lag time of one event is evaluated
180 as the time difference between the mass centres of the hyetograph and the hydrograph.
181 Evolution of the lag time can possibly reveal changes in mechanisms and processes governing
182 the runoff generation and transportation in a catchment. For instance, the lag time in an area
183 drained with sewer pipes is much shorter than that in a naturally drained area of a comparable
184 size and slope.

185 **3.4 Conceptual urban rainfall-runoff model**

186 Noting that the simple parameters defined in the above section are directly calculated from
187 rainfall and runoff data, ignoring the non-linear complex real rainfall-runoff mechanisms may
188 create bias in characterising the local process. Therefore, a conceptual urban rainfall-runoff
189 model is employed in this study to aid in identifying more relevant variables based on a more
190 comprehensive description of the hydrological process.

191 The conceptual urban rainfall-runoff model consists of a simple rainfall loss model and a
192 routing model of two cascaded linear reservoirs. The evaporation and evapotranspiration are
193 negligible at an event scale, and are thus not considered in the model structure using an event-
194 based approach. This model has been successfully applied in urban hydrology for small
195 impervious catchments drained by artificial sewer systems (e.g., Sun and Bertrand-Krajewski,
196 2013; Leonhardt et al., 2014). The rainfall loss model calculates net rainfall I_{net} by subtracting

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197 an initial loss L_{ini} (mm) and a proportional loss P_{cons} (-) during a rainfall event from gross
198 rainfall I .

$$I_{net}(t) = \begin{cases} 0 & \text{if } \int_{t=0}^t I dt \leq L_{ini} \\ I(t) (1 - P_{cons}) & \text{if } \int_{t=0}^t I dt > L_{ini} \end{cases} \quad (1)$$

199 Net rainfall is shifted with a time shift T_{shift} and is converted to inflow by multiplying it by the
200 effective catchment area A :

$$Q_{in}(t) = I_{net}(t - T_{shift}) \times A \quad (2)$$

201 In the runoff routing model, Q_{in} is routed through two cascaded linear reservoirs with the
202 same reservoir constants (K). A linear reservoir assumes that the outflow Q_{out} is linearly
203 related to the storage volume. The analytical solution of a linear reservoir model over the time
204 interval $[t - \Delta t, t]$ is

$$Q_{out}(t) = \exp\left(-\frac{\Delta t}{K}\right) Q_{out}(t - \Delta t) + \left[1 - \exp\left(-\frac{\Delta t}{K}\right)\right] Q_{in}(t) \quad (3)$$

205 The outflow from the first linear reservoir is then routed to the second reservoir as the inflow
206 and the outflow from the second reservoir is the output of the conceptual model. The
207 conceptual urban hydrological model contains four parameters, i.e., rainfall initial loss L_{ini} ,
208 rainfall constant proportional loss P_{cons} , time shift of inflow T_{shift} and reservoir constant of the
209 two reservoirs K .

210 3.5 Event-based conceptual hydrological model calibration

211 An event-based approach for hydrological process modelling is computationally efficient
212 when runoff is restricted to a short period after a storm event (Maneta *et al.*, 2007). This is

213 often the case in urban catchments equipped with storm sewer systems. A conceptual
214 hydrological model is often too simple to cover all conditions of the catchment and it has to
215 adjust itself (by adjusting model parameters) to represent different conditions. As a
216 consequence, model parameters are usually temporally different for varied rainfall-runoff
217 events. The dynamics of model parameters identified from event-based model calibration
218 using measured rainfall and runoff data thus possibly represent temporal catchment
219 characteristics and conditions. For instance, in our urban rainfall-runoff conceptual model, the
220 initial loss roughly indicates the antecedent weather condition of an event; the proportional
221 loss is probably an indicator of imperviousness; the time shift and reservoir constant are
222 related to the time of the catchment responding to rainfall. These model parameters can
223 further be used to study the evolution of long-term catchment properties.

224 The model is calibrated using the DREAM algorithm (Vrugt et al., 2008), which searches for
225 optimal parameters based on the Monte Carlo Markov Chain method. The effectiveness of
226 DREAM in calibrating hydrological models has been demonstrated by many studies in the
227 literature (e.g., Schoups *et al.*, 2010).

228 **3.6 Time of concentration estimated from conceptual rainfall-runoff model parameters**

229 The time of concentration, which is usually defined as the time of water flowing from the
230 point with the longest temporal flow path within a catchment to the catchment outlet, also
231 measures the response time of a catchment to a rain event. The time of concentration is an
232 important concept in hydrology because many practical designs and operation strategies rely
233 on the prediction of the catchment response time. The most common method to estimate the
234 time of concentration is via the identification of the flow path and the time of concentration is
235 the travel time of flows through the flow path. In this study, the time of concentration is
236 computed as the length of a unit hydrograph, which is the response of a watershed (in terms of

237 runoff volume and timing) to the input of a unit of rainfall. Once the urban hydrological
238 model is calibrated for a specific event, its unit hydrograph can be determined as a function of
239 two calibrated model parameters (i.e., the time shift and reservoir constant). More specifically,
240 a unit depth of net rainfall is input into the urban rainfall-runoff model (Eqs. (2) and (3)) with
241 the two calibrated model parameters, and the model output is its corresponding unit
242 hydrograph. Because a unit hydrograph from the linear reservoir model has a very long
243 recession limb, the time of concentration is estimated as the duration when 95% water volume
244 reaches the watershed outlet (a higher percentage of volume generally does not change the
245 relative magnitudes of the time of concentration from different hydrographs).

246 **3.7 Uncertainty in trend analysis due to noisy events**

247 Due to various reasons (e.g., measurement uncertainty, data errors and uncertainty in model
248 calibration), there might be erroneous values (from a noisy event) in data series. To study the
249 influence of the erroneous values on the trend detection results, uncertainty in trend detection
250 results due to erroneous values in data series is examined. One synthetic noisy value is
251 introduced into a data series at different positions. A noisy value is assumed to be extremely
252 big, small or median. An extremely big (small) value is even bigger (smaller) than the
253 maximum (minimum) value in the data series. The sensitivity of the trend detection results to
254 the magnitude and position of noisy values is then investigated by comparing the results of the
255 data series without and with an erroneous value.

256 **4 Results and discussion**

257 **4.1 Rainfall-Runoff event characteristics**

258 A total number of 692 significant events in Chassieu and 584 significant events in La Lechere
259 have been identified with complete one-minute or two-minute rainfall time series. A total
260 number of 584 and 442 runoff events are identified with complete runoff data with mean flow

261 over 5 L/s in Chassieu and La Lechere, respectively. The conceptual urban hydrological
262 model described above is calibrated to fit the rainfall and runoff data for each specific event
263 (see Section 4.3 for more details on the model calibration results). Most events (477 events in
264 Chassieu and 398 events in La Lechere) can be satisfactorily described by the conceptual
265 urban rainfall-runoff model with a Nash-Sutcliffe (NS) model efficiency coefficient over 0.7.
266 However, for a small number of events, the conceptual urban rainfall-runoff model produces
267 outputs with significant discrepancies from the measured data. This is likely due to errors
268 either in rainfall or runoff measurements (e.g., catchment areal rainfall not captured by point
269 measurement, Leonhardt et al., 2014) or the simple assumption of a constant baseflow. Only
270 events that can be satisfactorily described by the conceptual urban rainfall-runoff model are
271 considered for the following trend analysis. Fig. 1 shows the rainfall depth and duration of all
272 rainfall events and selected events that can be satisfactorily described by the conceptual urban
273 rainfall-runoff model.

274 Table 1 summarizes some statistical characteristics of the rainfall and runoff variables of the
275 selected events in the two catchments. The runoff-based variables are considered after
276 subtracting the baseflow, because this study is only concerned with the fast response of the
277 urban areas to rainfall. Big rainfall events were observed with a maximum rainfall depth of
278 134.6 mm in Chassieu and 91.4 mm in La Lechere. The rainfall and runoff variables were
279 generally distributed over wide ranges, with relative standard deviations typically over 1,
280 indicating positively skewed distributions of the variables, which are consistent with previous
281 findings (Brezonik and Stadelmann, 2002).

282 **4.2 Trend analysis of simple variables without modelling**

283 Variables of the selected events based on simple data analysis, i.e., baseflow, runoff
284 coefficient and lag time, are shown in Fig. 2 for the two catchments. Their statistical
285 characteristics are also summarized in Table 1.

286 In Chassieu, the baseflow values are mostly under 25 L/s with a median value of 2.0 L/s. Only
287 a few values in the latter years are over 25 L/s. Values of the runoff coefficient are between
288 0.03 and 0.81, with a median value of 0.30. The wide range of the runoff coefficient can be
289 explained by influential factors such as initial loss and dry weather flows, which are event-
290 specific. The lag time also covers a large range, mostly between 20 and 200 minutes with a
291 median of 77 minutes and with two negative values. The negative lag time of one event is
292 likely due to errors in rainfall and runoff measurements and the assumption of a constant
293 baseflow. The lag time varies depending on the profiles of the hyetograph and hydrograph,
294 due to the non-linear relationship between rainfall and runoff and possibly varied temporal
295 hydrological regimes.

296 In La Lechere, the median baseflow is 7.2 L/s and most values are in the interval of [0, 100].
297 One event with an extreme baseflow (over 300 L/s) occurred at the end of 2008, which can be
298 explained by a rainfall event of 73.4 mm ending only 15 hours before it, discharging high
299 natural flow from rural areas. The runoff coefficient is distributed across a range of [0.01, 0.3],
300 with a median value of 0.04. The generally low runoff coefficient (in comparison with that of
301 Chassieu) is found because only CSOs contribute to the considered runoff in La Lechere. The
302 median lag time is 110 minutes, with the range in [-50, 405] minutes.

303 Table 2 lists trend detection results for different rainfall and runoff variables. The original or
304 modified Mann-Kendall test is applied according to the significance of the autocorrelation test.
305 For both catchments, no trend is found for most rainfall-based variables, including depth,
306 duration and mean intensity. A relatively low *P*-value of 3.2% is obtained for the rainfall
307 duration in La Lechere, which is significant at the 5% significance level, but is still above the
308 less strict 1% significance level. In addition, the trend test is performed on many other rainfall
309 variables in addition to those listed in Table 2 (e.g., rainfall depth and intensity in a specific

310 duration). The results indicate no trend in any rainfall-based variables. There is likely no trend
311 in the rainfall variables (the driver of the hydrological process) for the study period.

312 For the urban runoff-based variables, data series of the runoff volume and mean runoff flow
313 are investigated. According to the original or modified Mann-Kendall test, all variables
314 present an increasing trend with *P*-values on the order of 1% or lower. The mean urban runoff
315 flow rate increases by 3.1 L/s in Chassieu and 0.7 L/s in La Lechere on average per year.

316 As a result of the relatively stable rainfall and increasing runoff, an increasing trend is
317 detected in the runoff coefficient in both catchments with very low *P*-values (on the order of
318 10^{-11} in Chassieu and 10^{-3} in La Lechere). The overall increasing rates of the runoff
319 coefficient are evaluated as 0.012 and 0.002 per year in Chassieu and La Lechere, respectively.

320 The increasing runoff coefficient is likely due to growing imperviousness caused by
321 urbanization in both catchments. In Chassieu, a comparison of aerial views at the beginning
322 and end of the study period shows more buildings being constructed, which led to increasing
323 imperviousness during the study period (Sun et al., 2015). However, it is worth noting that
324 urbanization can only be regarded indicative to runoff coefficient changes, because
325 urbanization does not always lead to higher runoff volumes, particularly with the
326 implementation of low urban development (LID) techniques such as porous pavement,
327 infiltration trenches and green roofs. In contrast, the lag time seems not to present a trend,
328 indicating no significant change in the travel time of flows in the catchments.

329 An increasing trend in the baseflow is confirmed in Chassieu with a *P*-value of 2.3%,
330 indicating more industrial wastewater draining into the system, whereas no trend is detected
331 in the baseflow in La Lechere, implying a relatively stable rural flow in this area.

332 **4.3 Conceptual urban rainfall-runoff model based analysis**

333 An event-based calibration is implemented for all of the available rainfall-runoff events in the
334 two catchments based on measured rainfall and runoff data. The optimal model parameters for
335 each event are identified using the DREAM algorithm based on 10^4 model evaluations. The
336 search ranges of the model parameters, which are determined based on catchment properties,
337 are given in Table 3. Only events that are satisfactorily described by the conceptual rainfall-
338 runoff model with an NS value over 0.7 are considered. Table 3 also lists the summary
339 statistics of the optimal model parameters. Fig. 3 shows the optimal model parameters. The
340 parameter of initial loss is broadly distributed in the search range of [0-2mm] or [0-3mm] in
341 the two catchments, with several events reaching the limits. However, the limits are not
342 extended to reflect the physical reality in the catchments. The proportional loss is also event-
343 dependent and distributed in a wide range with a median of 0.65 in Chassieu and 0.88 in La
344 Lechere. This parameter can be roughly linked to the runoff coefficient, with the absolute
345 values of the correlation coefficients of 0.73 in Chassieu and 0.83 in La Lechere. The reservoir
346 constant and time shift reveal the response time of the catchments to rainfall events. These
347 two parameters also show great variability.

348 The temporal variability of the model parameters implies that the lumped conceptual urban
349 rainfall-runoff model is too simple to cover all conditions encountered by all of the events in
350 the urban catchments, which is consistent with previous findings (Maneta et al., 2007). The
351 calibrated parameters reveal the temporal hydrological regime/conditions during one specific
352 event. However, the variability of optimal model parameters may also result from other
353 reasons, leading to bias in some model parameter estimates in the lumped conceptual urban
354 rainfall-runoff model. For instance, errors in areal rainfall (represented by point measurements)
355 and runoff measurements lead to biased calibration results, as in calibration, the model
356 parameters are adjusted to make the lumped model outputs match the measurements.
357 Additionally, the model parameters are correlated (e.g., Sun and Bertrand-Krajewski, 2013).

358 The initial loss and proportional loss are negatively correlated; the reservoir constant and the
359 time shift are also negatively correlated. Simultaneously adjusting correlated parameters gives
360 equivalent model performances.

361 The time of concentration for each event is evaluated from the calibrated reservoir constant
362 and time shift (Fig. 4). The median time of concentration in Chassieu is 92 minutes and most
363 values are in the range of [10-400]. The time of concentration in La Lechere covers a range of
364 [24, 724] minutes and the median is 132 minutes.

365 Fig. 5 shows the scatter points of the lag time directly derived from the data and the time of
366 concentration estimated from calibrated urban rainfall-runoff model parameters. These two
367 quantities both indicating the response time of the urban catchments to rainfall events are
368 highly correlated. However, the relation between these two variables also shows some
369 randomness, resulting from the non-linear relation between rainfall and runoff and the
370 different methods with which the two parameters are calculated.

371 Assuming that other factors listed above (e.g., errors in rainfall and runoff data, uncertainty in
372 calibration and parameter correlation) leading to temporal variation of model parameters are
373 random without a trend, trend analysis of model parameters can still provide useful
374 information on hydrological regime evolution in the two catchments. Table 4 lists the trend
375 detection results of optimal model parameters along with the time of concentration. The initial
376 loss does not present a trend in both catchments, indicating stable initial conditions of rainfall
377 events, which are linked to antecedent dry periods and precedent events. A decreasing trend is
378 found in the constant loss in both catchments with low P -values, which is consistent with the
379 detected increasing trend in the runoff coefficient in the above analysis due to urban
380 development in the catchments. The constant loss is evaluated with a decreasing rate of
381 approximately 0.014 per year in Chassieu and 0.005 in La Lechere. These figures are close to

382 the values of the increasing rates in the runoff coefficient estimated using the simple data
383 analysis method (see Table 2).

384 The reservoir constant and lag time in Chassieu seem to not contain a trend according to the
385 Mann-Kendall method, suggesting that the routing function governing runoff generation does
386 not have a significant change in Chassieu. In contrast, the reservoir constant possibly presents
387 a decreasing tendency in La Lechere with a P -value under 5%. Consequently, the time of
388 concentration evaluated based on this parameter in La Lechere is also detected with a
389 declining trend of approximately 3.5 minutes per year. This is consistent with the common
390 sense notion that urbanization leads to a shorter time of concentration because an artificial
391 drainage system often transports stormwater much faster than a natural water course. In the
392 study period of ten years, a decrease of 35 minutes in the concentration time is expected,
393 which is non-negligible in comparison with the median time of concentration of 132 minutes.
394 However, the trends in both variables are rejected with the stricter 1% significance level.
395 Further data are required in order to confirm the trend in these variables.

396 **4.4 Sensitivity of noisy events to trend detection results**

397 Due to the various reasons presented above (e.g., the lumped and simplified model
398 representing the complex rainfall-runoff process, errors in rainfall and runoff measurements
399 and the correlation between model parameters in calibration), parameters characterizing local
400 hydrology obtained from data analysis and model calibration for some events may be
401 erroneous. For instance, the negative lag time and the reservoir constant of three events in La
402 Lechere close to 240 minutes (which is the search limit) are likely to be erroneous. This
403 section investigates the influence of the presence of noisy events (with erroneous values) in
404 the data series on the trend detection results using the Mann-Kendall test.

405 Four data series of optimal model parameters are used to study the sensitivity of trend
406 detection results to noisy values. The original data series are considered as the comparison
407 benchmarks, assuming that they do not contain any erroneous data. Fig. 6 shows the P -values
408 of different cases with one noisy value together with the P -value of the original data series. It
409 is clear that the influence of a noisy event depends both on the magnitude and the position of
410 the noisy event.

411 In Fig. 6 (a), the data series of the initial loss in Chassieu, which does not present a trend is
412 studied. The original Mann-Kendall method is used because the autocorrelation effect in the
413 data series is insignificant. An extreme noisy value introduced at the two sides of the data
414 series leads to the most significant change in the P -value. The influence of a noisy value is
415 negligible when it is in a middle position in the data series. A noisy median value does not
416 significantly affect the P -value at any position in the data series. The P -value changes
417 gradually as a noisy event moves in the data series.

418 In Fig. 6(b), the data series of the constant loss in Chassieu, which presents a decreasing trend
419 as indicated by the original Mann-Kendall method, is studied. An extremely high noisy value
420 located at the beginning of the data series leads to a lower P -Value, as expected. An extreme
421 noisy value in the middle positions of the data series and a noisy median value at any position
422 do not have significant impacts on the P -value.

423 In Fig. 6 (c) and (d), data series of the constant loss and time shift in La Lechere with
424 significant autocorrelation are studied using the modified Mann-Kendall method. Different
425 from those in Fig. 6 (a) and (b), the P -values do not change monotonously as the position of a
426 noisy value changes gradually in a data series, due to the influence of the autocorrelation
427 coefficients incorporated in the modified Mann-Kendall test. The relation between the P -
428 value and the position of an erroneous value is rather random. The most significant change in

429 a P -value due to an extreme noisy value does not necessarily occur when it is located at the
430 two sides of the data series. In both cases, the introduction of one erroneous value does not
431 change the trend detection results.

432 Furthermore, the impact of the number of noisy values on the trend detection results using the
433 original Mann-Kendall method is also studied. The trend detection results from the original
434 Mann-Kendall method are most sensitive to extreme erroneous values at the two sides of the
435 data series. Therefore, the impact of the number of noisy values is studied here by examining
436 cases with extreme noisy values introduced in the beginning of data series. Fig. 7 shows the
437 results. In Fig. 7(a), for the data series of the initial loss (containing 477 events) in Chassieu,
438 which does not present a trend, a trend will only be detected with more than 9 extremely small
439 noisy events or 21 extremely large events introduced in the beginning of the data series. In Fig.
440 7(b), for the constant loss data series in Chassieu presenting a significantly decreasing trend
441 with a P -value of $2.7 \times 10^{-9}\%$, the Mann-Kendall test only gives a different indication of trend
442 absence when over 32 extremely small noisy values are introduced.

443 Based on the above analysis, a different trend result generally requires a number of extreme
444 erroneous values at one side of a data series. The Mann-Kendall method, which is a function
445 of the ranks of the observations rather than their actual values, is not sensitive to a few noisy
446 values. Therefore, in this study, the trend detection results using the original Mann-Kendall
447 method are probably reliable regardless of a few possible noisy values in the data series.

448 However, the sensitivity of the trend detection results from the modified Mann-Kendall
449 method seems to be more complicated due to the altered autocorrelation coefficients.

450 **5. Conclusions**

451 It is important to assess any hydrological trend (if one exists) in urban catchments because the
452 design and operation of urban stormwater projects aiming to reduce the adverse impact of

453 stormwater should take into account possible changes in urban hydrology patterns. This paper
454 addresses hydrological trend analysis in urban catchments. Using rainfall and runoff data and
455 a conceptual rainfall-runoff model, lumped parameters that aggregate distributed spatial
456 information in the urban/peri-urban catchments are analysed to reveal the global evolution of
457 the hydrological responses (noting that distributed processes, factors and properties on smaller
458 scales in local hydrology are beyond the discussion). The evolution of aggregate hydrologic
459 relevant parameters is useful in indicating changes in local hydrology and needs to be
460 considered in urban stormwater management. The original and modified Mann-Kendall
461 methods are applied for trend detection in data series in two catchments in France, i.e.,
462 Chassieu and La Lechere, and there seems to be no difficulty of applying the methodology to
463 other urban catchments. Based on the application results for approximately one decade of data,
464 the following conclusions can be drawn:

465 1. A trend is absent in the driving force (precipitation) of the rainfall-runoff processes in both
466 catchments in the suburbs of Lyon for the study period.

467 2. An increasing trend is found in the urban runoff variables. On average, the mean runoff
468 flow rate increases by 3.1 L/s in Chassieu and 0.7 L/s in La Lechere per year.

469 3. As a result of the relatively stable rainfall and increasing urban runoff volumes, the runoff
470 coefficient presents an increasing trend in both catchments, probably due to growing
471 imperviousness caused by urbanization, even in Chassieu, where the catchment is already
472 very densely urbanized, rather than climate change factors. However, it is worth noting that
473 nowadays urbanization does not automatically lead to more imperviousness and increasing
474 catchment outflow. The influence of urbanization development on the local hydrological
475 processes is much more complicated than simple imperviousness evolution because it is
476 highly dependent on the detailed changes and processes. For instance, in the LID context,

477 when urban areas expand, water on the impervious surface can be connected to vegetated
478 areas or infiltration devices; some rain can be retained via green roofs. In addition, the
479 efficiency of an LID device may decline over time (e.g., when an infiltration system is
480 clogged), leading to a part of stormwater back to catchment outflow. Therefore, the evolution
481 of stormwater quantities is difficult to be precisely inferred only from urbanization
482 information. The methodology developed in this study provides the most direct evidence of
483 the elevated runoff coefficient in urban/peri-urban catchments.

484

485 4. Optimal parameters of a conceptual urban rainfall –runoff model obtained from calibration
486 using an event-based approach are used to represent the temporal hydrological regime.
487 Though temporal variation of optimal model parameters is also affected by other factors such
488 as errors in rainfall and runoff measurements, uncertainty in calibration and parameter
489 correlation, the variance due to these factors is assumed to be random. The trend analysis
490 results of these model parameters therefore reveal local hydrology evolution. No trend is
491 present in the initial loss. A decreasing trend is found in the constant proportional loss in both
492 catchments, which is consistent with the increasing runoff coefficient. The time of
493 concentration in Chassieu does not exhibit a trend, whereas it seems to decrease by 3.5
494 minutes per year in La Lechere. The trend in the time of concentration in La Lechere needs to
495 be confirmed with further data.

496 5. The sensitivity analysis indicates that the original Mann-Kendall method is not sensitive to
497 a few noisy values in the data series. Therefore, the trend detection results from the original
498 Mann-Kendall method are reliable, regardless of a few possible erroneous data. However, the
499 relation between trend detection results and noisy values using the modified Mann-Kendall
500 method is rather complicated and difficult to quantify.

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506

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585 **Figure captions**

586 Fig 1. All rainfall events and events that can be satisfactorily described by rainfall-runoff
587 model: (a) Chassieu; (b) La Lechere

588 Fig 2. Simple variables in chronological order: (1) Chassieu; (2) La Lechere

589 Fig 3. Optimal model parameters of conceptual urban rainfall-runoff models using event-
590 based calibration: (1) Chassieu; (2) La Lechere

591 Fig 4. Time of concentration from calibrated model parameters: (a) Chassieu; (b) La Lechere

592 Fig 5. Scatter plots of lag time and time of concentration: (a) Chassieu; (b) La Lechere

593 Fig 6. Sensitivity of P-values to one noisy value: (a) the initial loss in Chassieu; (b) the
594 constant loss in Chassieu; (c) the constant loss in La Lechere; (d) the time shift in La Lechere

595 Fig 7. Sensitivity of P-values to a number of extreme events introduced in the beginning of
596 data series using the original Mann-Kendall method: (a) the initial loss in Chassieu; (b) the
597 constant loss in Chassieu.

598

599

600 **Table captions**

601 Table 1. Statistical characteristics of event-based variables in Chassieu and La Lechere

602 Table 2. Trend detection results on simple variables without modeling

603 Table 3. Parameters of conceptual rainfall-runoff model in the two catchments

604 Table 4. Trend detection results for the parameters in the conceptual urban rainfall-runoff

605 model

606

607 Table 1. Statistical characteristics of event-based variables in Chassieu and La Lechere

Catchment	Variables	Characteristics	Median [min-max]	Mean (standard deviation)	
Chassieu (477 events)	Rainfall	Depth (mm)	4.8 [1.2-134.6]	9.0 (12.5)	
		Duration (h)	4.7 [0.6-42.6]	6.8 (6.3)	
		Mean intensity (mm/h)	1.00 [0.21-23.1]	1.70 (2.12)	
	Runoff deducted with baseflow	Total volume ($\times 10^3 \text{ m}^3$)	2.00[0.16-60.7]	4.29 (6.68)	
		Average rate (L/s)	58.2 [0.90-805.7]	98.7 (112.0)	
	Baseflow	(L/s)	2.0 [0.0-46.8]	4.5 (5.4)	
	Rainfall-runoff process	Runoff coefficient (-)	0.30 [0.03-0.81]	0.31 (0.10)	
		Lag time (min)	77.1[-23.0-207.4]	81.1 (33.5)	
	La Lechere (398 events)	Rainfall	Depth (mm)	7.4 [2.0-91.4]	10.6 (10.1)
			Duration (h)	5.9 [0.5-33.8]	7.7 (6.4)
Mean intensity (mm/h)			1.4 [0.3-16.3]	2.0 (2.0)	
runoff deducted with baseflow		Total volume ($\times 10^3 \text{ m}^3$)	0.93 [0.10-28.0]	2.07 (3.34)	
		Average rate (L/s)	24.3 [5.0- 410.6]	44.7 (55.3)	
Baseflow		(L/s)	7.2 [0-317.6]	15.8 (25.6)	
Rainfall-runoff process		Runoff coefficient (-)	0.04 [0.01- 0.30]	0.05 (0.04)	
		Lag time (min)	110 [-50-405]	121 (57)	

608

609 Table 2. Trend detection results on simple variables without modeling

	Variable	Parameter	Mann-Kendall test	P-value (%)	Slope (-/year)
Chassieu (477 events)	Rainfall	Depth (mm)	Original	10.2	-
		Duration (h)	Original	58.2	-
		Mean intensity (mm/h)	Modified	12.5	-
	Runoff without baseflow	Total runoff volume (m ³)	Original	0.1 ^{**}	98.7
		Mean runoff flow rate (L/s)	Original	1.2×10 ^{-2**}	3.1
	Rainfall-runoff processes	Runoff coefficient (-)	Original	1.4×10 ^{-9**}	0.012
		Lag time (min)	Modified	43.6	-
	Other	Baseflow (L/s)	Modified	2.3 [*]	0.32
	La Lechere (398 events)	Rainfall	Depth (mm)	Original	34.6
Duration (h)			Original	3.2 [*]	0.18
Mean intensity (mm/h)			Original	6.0	-
Runoff		Total runoff volume (m ³)	Original	0.9 ^{**}	35.8
		Mean runoff flow rate (L/s)	Original	3.7 [*]	0.7
Rainfall-runoff processes		Runoff coefficient (-)	Modified	0.2 ^{**}	0.002
		Lag time (min)	Modified	68.5	-
Other		Baseflow (L/s)	Modified	55.6	-

610 The P-value is remarked with * when it is significant at 5% level, with ** when it is significant
 611 at 1% level.
 612

613

614 Table 3. Parameters of conceptual rainfall-runoff model in the two catchments

parameter	Chassieu			La Lechere		
	Search range	Median [min-max]	Mean (standard deviation)	Search range	Median [min-max]	Mean (standard deviation)
Initial loss (mm)	[0, 2]	0.67 [0.0-2.0]	0.79 (0.59)	[0, 3]	1.6 [0.0-3.0]	1.6 (1.1)
Constant loss (-)	[0, 1]	0.65 [0.0-0.98]	0.64 (0.14)	[0, 1]	0.88 [0.25,0.97]	0.86 (0.09)
Reservoir constant (min)	[1, 120]	15.5 [1.0-90.2]	19.0 (12.0)	[1,240]	26.6 [2.4-240]	36.3 (34.9)
Time shift (min)	[1,60]	14.0 [1.2-60.0]	16.1 (11.9)	[1,120]	2 [0-66]	4.5 (7.0)

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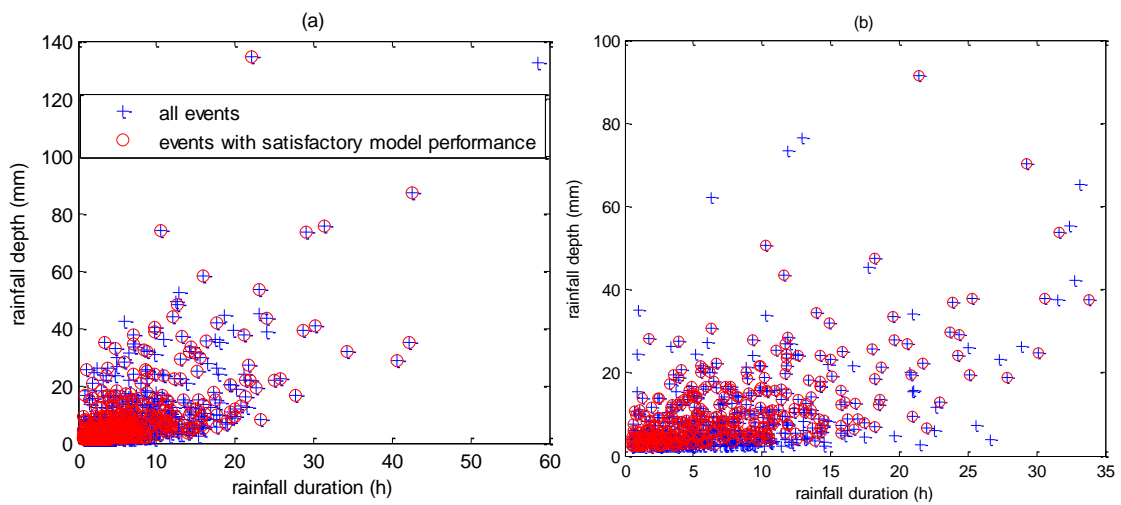
616

617 Table 4 Trend detection results for the parameters in the conceptual urban rainfall-runoff
 618 model

		Parameter	Mann-Kendall test	P-value (%)	Slope (-/year)
Chassieu (477 events)	Model parameters	Initial loss	Original	43.2	-
		Constant loss	Original	2.7×10^{-9} **	-0.014
	Other parameters	Reservoir constant	Modified	39.9	-
		Time shift	Modified	88.5	-
		Time of concentration (min)	Modified	99.1	-
La Lechere (398 events)	Model parameters	Initial loss	Modified	19.2	-
		Constant loss	Modified	0.01**	-0.005
	Other parameters	Reservoir constant	Modified	0.3**	-0.8
		Time shift	Original	97.2	-
		Time of concentration (min)	Modified	2.0*	-3.5

619

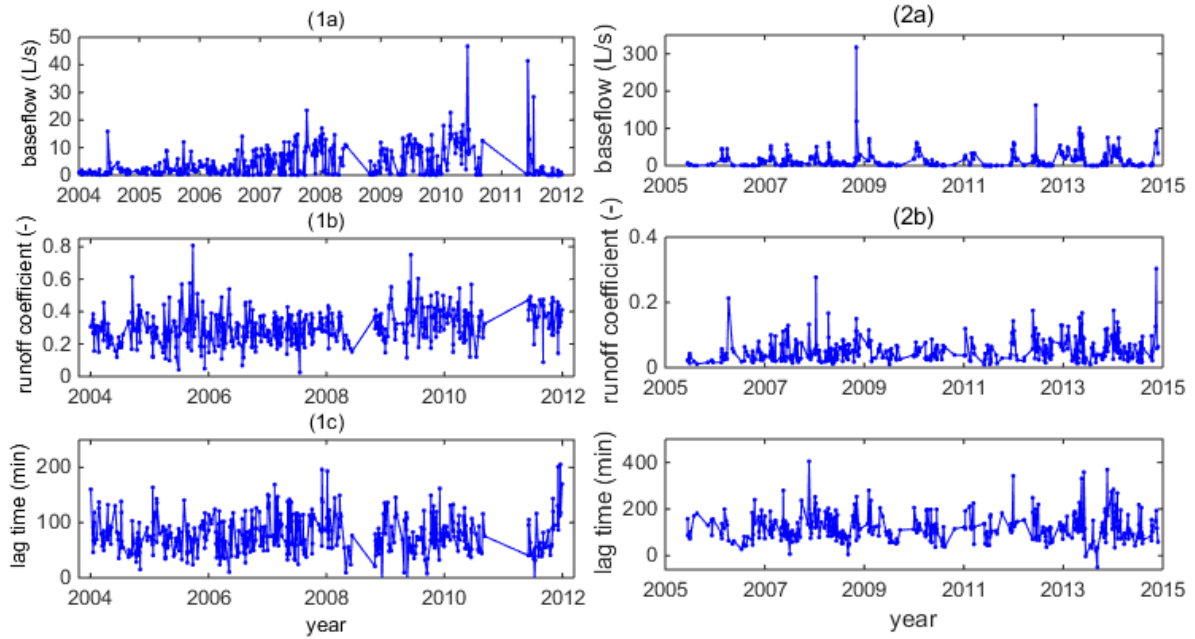
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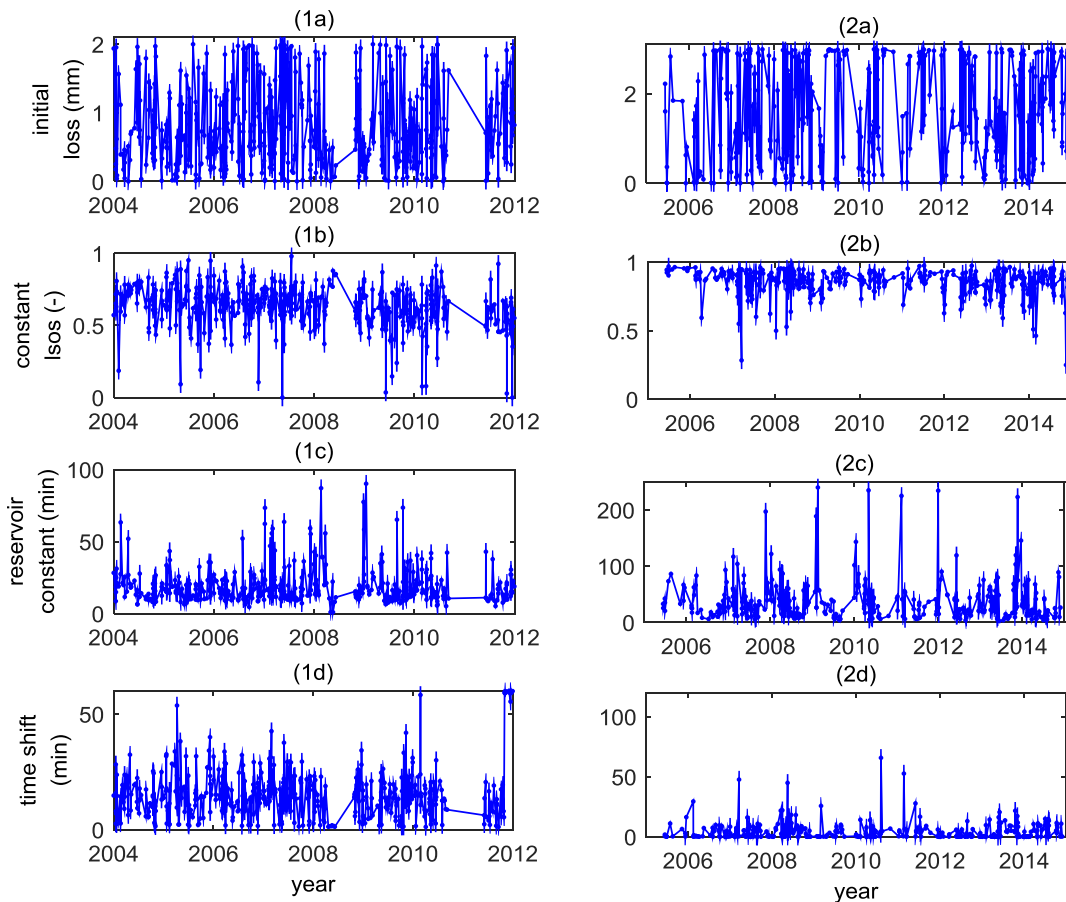
622 Fig. 1. All rainfall events and events that can be satisfactorily described by rainfall-runoff
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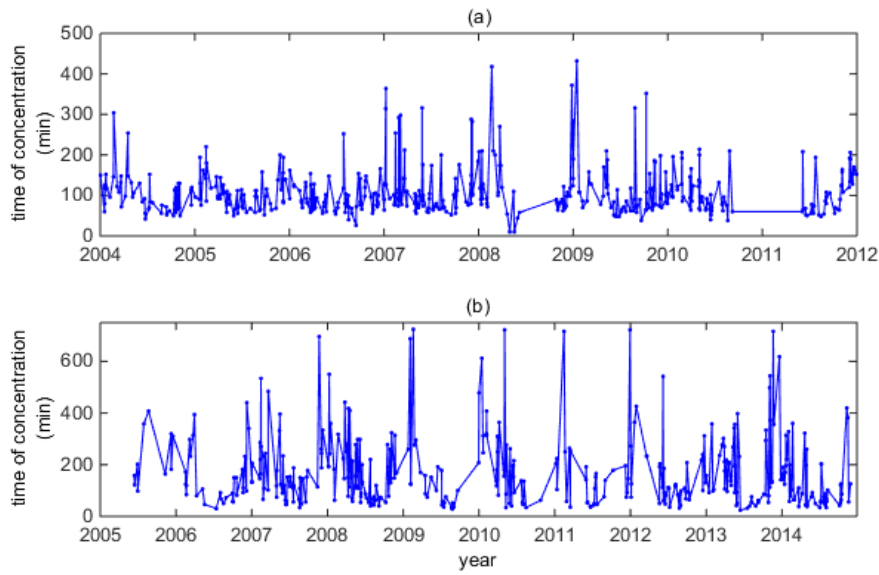
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625 Fig. 2 Simple variables in chronological order: (1) Chassieu; (2) La Lechere



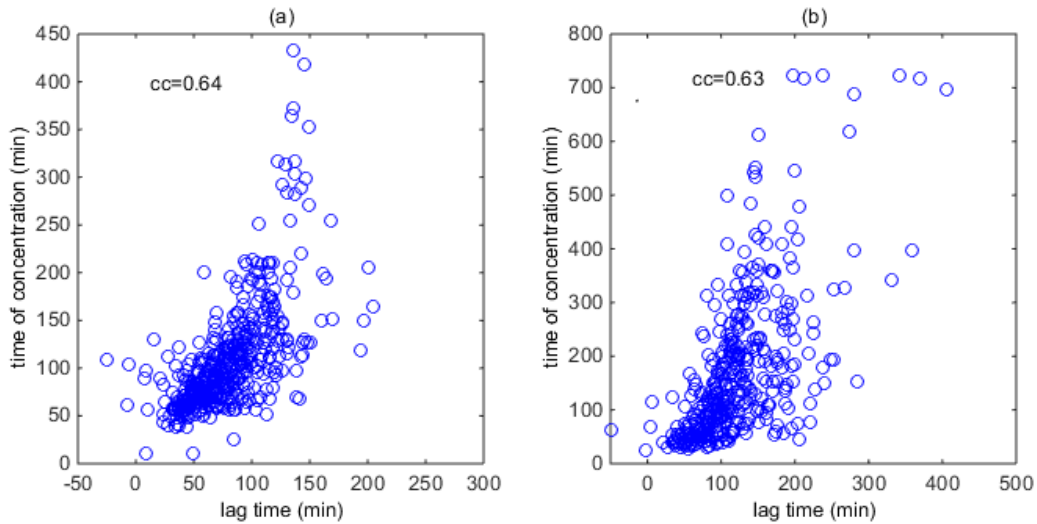
626

627 Fig. 3 Optimal model parameters of conceptual urban rainfall-runoff models using event-
628 based calibration: (1) Chassieu; (2) La Lechere



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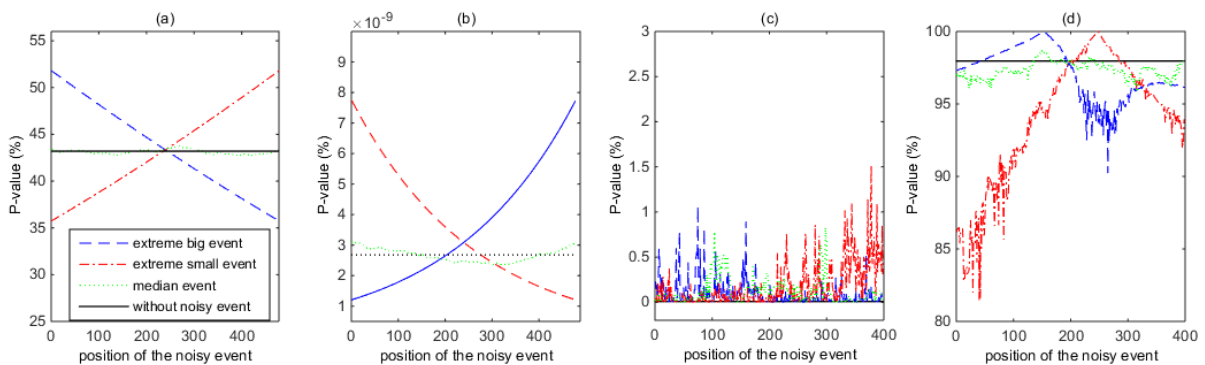
630 Fig. 4 Time of concentration from calibrated model parameters: (a) Chassieu; (b) La Lechere



631

632 Fig. 5 Scatter plots of lag time and time of concentration: (a) Chassieu; (b) La Lechere

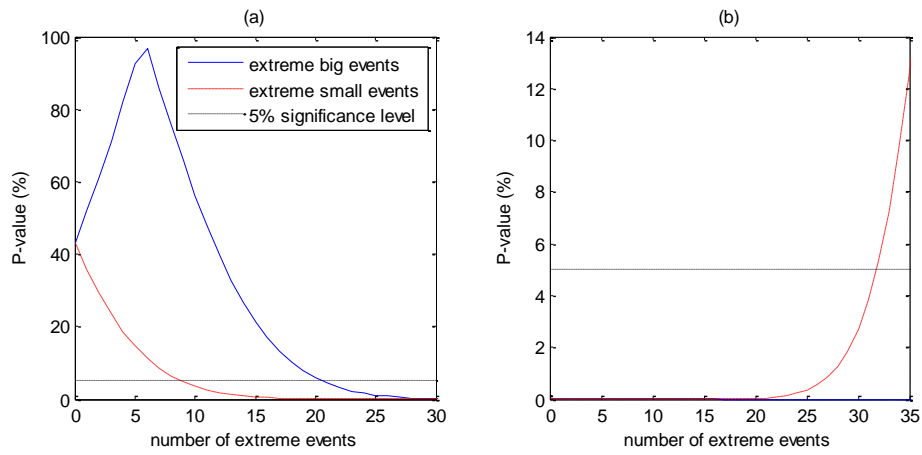
633



634

635 Fig. 6 Sensitivity of P-values to one noisy value: (a) the initial loss in Chassieu; (b) the
 636 constant loss in Chassieu; (c) the constant loss in La Lechere; (d) the time shift in La Lechere

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637

638 Fig . 7 Sensitivity of P -values to a number of extreme events introduced in the beginning of
639 data series using the original Mann-Kendall method: (a) the initial loss in Chassieu; (b) the
640 constant loss in Chassieu.

641