

1 ***Temporal scaling phenomena in groundwater-floodplain systems using robust detrended***
2 ***fluctuation analysis***

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12

13 **Abstract**

14 In order to determine objectively the fractal behaviour of a time series, and to facilitate potential
15 future attempts to assess model performance by incorporating fractal behaviour, a multi-order
16 robust detrended fluctuation analysis (r-DFAn) procedure is developed herein. The r-DFAn
17 procedure allows for robust and automated quantification of mono-fractal behaviour. The fractal
18 behaviour is quantified with three parts: a global scaling exponent, crossovers, and local scaling
19 exponents. The robustness of the r-DFAn procedure is established by the systematic use of robust
20 regression, piecewise linear regression, Analysis of Covariance (ANCOVA) and Multiple Comparison
21 Procedure to determine statistically significant scaling exponents and optimum crossover locations.
22 The MATLAB code implementing the r-DFAn procedure has also been open sourced to enable
23 reproducible results.
24 r-DFAn will be illustrated on a synthetic signal after which is used to analyse high-resolution
25 hydrologic data; although the r-DFAn procedure is not limited to hydrological or geophysical time
26 series. The hydrological data are 4 year-long datasets (January 2012 to January 2016) of 1-minute

27 groundwater level, river stage, groundwater and river temperature, and 15-minute precipitation and
28 air temperature, at Wallingford, UK. The datasets are analysed in both time and fractal domains. The
29 study area is a shallow riparian aquifer in hydraulic connection to River Thames, which traverses the
30 site. The unusually high resolution datasets, along with the responsive nature of the aquifer, enable
31 detailed examination of the various data and their interconnections in both time- and fractal-
32 domains.

33

34 **Keywords:** robust detrended fluctuation analysis; detrended fluctuation analysis; fractal behaviour;
35 Hurst Phenomenon; Time series analysis; high resolution hydrological data;

36

37 **Introduction**

38 In the field of hydrology, the onset of the study of fractal behaviour of hydrological time series is
39 marked with Hurst's investigation of the storage capacity of the Aswan High Dam in Egypt in 1951
40 (Hurst 1956, Hurst 1951). This sparked further investigation of what later came to be known as the
41 'Hurst Phenomenon' (Hurst 1951). The initial mathematical representation of the Hurst Phenomenon
42 was described in terms of range, standard deviation and the number of samples considered. However,
43 this relationship evolved into: $E\{X(T)\} \propto T^H$ with $H \neq 0.5$, where $X(T)$ is the aggregated series
44 at scale T and H is the Hurst Exponent (Bras, Rodriguez-Iturbe 1985). Of course, the relationship
45 follows a power law and is linearly related to other measures of fractal behaviour such as the power-
46 law exponent of the spectral density estimate and the scaling exponent α determined by detrended
47 fluctuation analysis.

48 The mathematician Benoit Mandelbrot introduced a different concept to the Hurst Phenomenon that
49 infuses the self-similarity property of fractals with that of Hurst (Mandelbrot 1982). Mandelbrot
50 introduced the term 'fractional noises' in 1968 to unify the different terms developed over time and
51 across the different fields that describe series with long-term interdependence (Mandelbrot, Van Ness

52 1968). Hence the term 'Fractal behaviour' will be used in this paper to refer to the 'Hurst phenomenon'
53 and 'long-term memory'; terms which are more common to hydrologists.

54 Evidently, fractal behaviour of time series has been investigated in various fields and a wide variety
55 of techniques have been used to quantify it. Fractal behaviour has been studied in the fields of,
56 amongst others, pharmacology: long-term correlations of DNA (Peng, Buldyrev et al. 1994);
57 cardiology: non-stationary heart beat time series (Peng, Havlin et al. 1995); earth sciences: ocean
58 wave height (Ozger 2011), temperature (Koscielny-Bunde, Bunde et al. 1996) and seismicity (Alvarez-
59 Ramirez, Echeverria et al. 2011); traffic control: traffic speeds time series (Shang, Lu et al. 2008), in
60 marine transportation (Chen, Tian et al. 2016), solar physics: sunspot time series (Sadegh Movahed,
61 Jafari et al. 2006), finance: the economy and stock market (Reboredo, Rivera-Castro et al. 2013)
62 (Zunino, Tabak et al. 2008, Caraianni 2012) and even in music (Dagdug, Alvarez-Ramirez et al. 2007,
63 Jafari, Pedram et al. 2012, Hennig, Fleischmann et al. 2011, Telesca, Lovallo 2012). Finally, it has
64 been widely used to investigate the fractal behaviour of hydrological systems, which is the focus of
65 this investigation.

66 A variety of techniques have been used to study the fractal behaviour of time series. These include
67 spectral analysis, wavelet analysis, rescaled-range (R/S), and detrended fluctuation analysis (DFA).
68 Among these techniques, DFA and spectral analysis are the most commonly used, with DFA being
69 the preferred technique by many researchers (Chen, Ivanov et al. 2002, Eichner, Koscielny-Bunde et
70 al. 2003, Zhang, Zhou et al. 2011, Hu, Ivanov et al. 2001, Matsoukas, Islam et al. 2000, Hu, Gao et al.
71 2009, Ozger 2011) due to ease of detecting changes in scaling when compared to spectral analysis.
72 Many hydrological time series are mono- and multi-fractal in nature with cut-offs in their scaling
73 regime, i.e. they exhibit crossovers (Little, Bloomfield 2010, Matsoukas, Islam et al. 2000, Li, Zhang
74 2007, Tessier, Lovejoy et al. 1996). Identifying these crossovers, or scaling breakpoints, is not
75 generally done in a systematic or objective way, if it is acknowledged at all (Little, Bloomfield 2010,
76 Zhang, Zhou et al. 2011, Zhu, Young et al. 2012, Williams, Pelletier 2015, Yu, Ghasemizadeh et al.
77 2016, Li, Mu et al. 2015, Condon, Maxwell 2014). In order to overcome this deficiency and to provide

78 a means for quantifying reliable mono-fractal behaviour that can be used for further analysis – such
79 as in conjunction with models or to infer causalities – this study presents a robust DFA procedure,
80 named r-DFA. The aim behind r-DFA is to identify statistically different scaling regions in a signal
81 along with the location of these changes, or crossovers, in a systematic way.

82 Even though fractal behaviour was found to be intrinsic to signals observed from diverse fields, a key
83 stage in its development is Hurst's investigation of the storage capacity of the Aswan High Dam in
84 Egypt in 1951. Analysing annual flows in the Nile, he noticed the clustering of high flows and low
85 flows in the hydrological time series, and how these variations were scaled with the time over which
86 they were considered. This effect came to be known as the Hurst Phenomenon (Hurst 1956, Hurst
87 1951) and appears to be a fundamental property of many natural and anthropogenic systems, as the
88 above examples show.

89 Hydrological and hydro-meteorological time series such as rainfall, river stage, river flow,
90 temperature and more recently, groundwater levels have been characterised as being fractal
91 (Eichner, Koscielny-Bunde et al. 2003, Zhang, Schilling 2004, Zhang, Yang 2010, Fraedrich, Larnder
92 1993, Gelhar 1974, Kavasseri, Nagarajan 2004, Li, Zhang 2007, Little, Bloomfield 2010, Zhu, Young et
93 al. 2012, Liang, Zhang 2013), however, high resolution hydrological datasets are generally not
94 available and this makes the study of the full range of fractal behaviour difficult. Among hydrological
95 variables, groundwater levels, in particular, are not generally monitored at very short time intervals
96 (such as one minute intervals), as for most purposes less frequent measurements are considered
97 sufficient to capture any variations of interest. Indeed, in many aquifers the forcing processes are
98 significantly damped such that there is very little value in monitoring at time intervals less than 1
99 day. However, this is not necessarily the case for shallow permeable aquifers, particularly if
100 hydraulically connected with a river. In such cases, fluctuations in recharge due to variations in
101 rainfall or changes in river stage during flood events can cause sub-daily groundwater level
102 variations which can only be studied with high resolution data.

103 After presenting the r-DFAn procedure, a synthesized mono-fractal signal will be used to illustrate r-
104 DFAn. In addition to this, high resolution, 1-minute and 15-minute, hydrological data from a study
105 site in Wallingford will be presented in the time domain and their fractal behaviour will be analysed
106 using r-DFAn. The datasets are: groundwater levels, river stage, groundwater temperature, river
107 temperature, precipitation and air temperature.

108 The sections that follow include an explanation of the r-DFAn procedure followed by a detailed
109 description of the study site and data collection and finally a presentation of the r-DFAn results along
110 with a general discussion and some conclusions.

111

112 **Methodology: r-DFAn procedure**

113 Among numerous methods developed for studying fractal behaviour, detrended fluctuation analysis
114 (DFA) is agreed to be a reliable method for non-stationary signals (Chen, Ivanov et al. 2002, Eichner,
115 Koscielny-Bunde et al. 2003, Zhang, Zhou et al. 2011, Hu, Ivanov et al. 2001, Matsoukas, Islam et al.
116 2000), among others). Nevertheless, in the case of mono-fractal signals that exhibit changes in there
117 scaling regimes, determining crossovers is subjective and seriously affects the reliability of mono-
118 fractal quantification.

119 Hence a procedure that includes DFA and statistical models was developed in order to overcome this
120 shortcoming and to automate the entire quantification process. The procedure, which will be named
121 r-DFAn, where n is the order of the detrending function, is explained below and illustrated on a
122 synthetic signal.

123 *Detrended fluctuation analysis*

124 DFA of first order (i.e. DFA1) was first proposed by (Peng, Buldyrev et al. 1994) when analysing
125 correlations in DNA. DFA is presented in the following five steps:

- 126 1. Let $y(t_i)$ be a measurement of variable y observed at equally spaced time intervals, t_i , for
127 N discrete times. Let \bar{y} be the mean of $y(t_i)$. Compute $Y(t_i)$ by subtracting the mean
128 from the time series and computing a cumulative sum:

129
$$Y(t_i) = \sum_{i=1}^N (y(t_i) - \bar{y}) \quad (1)$$

130 2. Divide $Y(t_i)$ into m non-overlapping segments each of length L so that $m = \text{int}\left(\frac{N}{L}\right)$.

131 Each segment will be notated as $Y_{j,k}(t_i)$ where $j=1,2,\dots,L$ and $k=1,2,\dots,m$, hence

132
$$i = (k-1)L + j.$$

133 3. Determine the variance ($F_k^2(L)$) of the fluctuation in each segment (Y_k) after subtracting a
 134 best-fit polynomial of order n ($P_{j,k}^n(t_i)$) from each segment. DFA_n refers to DFA detrending
 135 with polynomial of order n .

136
$$F_k^2(L) = \frac{1}{L} \sum_{j=1}^L (Y_{j,k} - P_{j,k}^n)^2 \quad \text{for } k=1,2,\dots,m \quad (2)$$

137 4. Determine an average variance measure for all segments of length L :

138
$$F(L) = \left[\frac{1}{m} \sum_{k=1}^m F_k^2(L) \right]^{1/2} \quad (3)$$

139 5. Repeat steps 1 to 4 for different values of L then plot $F(L)$ versus L on logarithmic axes
 140 to determine the scaling exponent (α) which is the slope of a best-fit line, as:

141
$$F(L) \approx L^\alpha \quad (4)$$

142 In this paper, α will be referred to as the global scaling exponent; the slope determined by ignoring
 143 the occurrence of any local changes in the scaling exponent. Robust regression (with a bi-square
 144 weight function) is used to determine α . This ensures that the scaling exponent so determined is
 145 based on residuals that are within predefined bounds.

146 *Determining scaling exponents and crossovers for mono-fractal signals*

147 As previously mentioned, changes in the slope of the scaling exponent (α) may be observed, which
 148 indicate mono-fractal behaviour with changes in the scaling regime. The time periods (L) where
 149 such changes occur are referred to as crossovers (Kantelhardt, Koscielny-Bunde et al. 2001, Hu,

150 Ivanov et al. 2001, Li, Zhang 2007). Even though DFA is a reliable method for identifying fractal
151 behaviour, determining the number and locations of crossovers, has been rather subjective.
152 After determining the global scaling exponent using robust regression, piecewise linear regression
153 will be used to optimise the locations of crossovers by minimising the least squares error between
154 the data and the fitted broken-line (i.e. the line with crossovers). The number of crossovers to be
155 fitted to the data are determined in order to give the maximum number of crossovers that produce
156 significantly different slopes based on a 95% significance level. This is determined by applying an
157 analysis of covariance (ANCOVA) and a multiple comparison procedure on the DFA results. The
158 number of crossovers are progressively increased until the method fails to yield any further
159 significant scaling exponents.

160 ANCOVA (the analysis of covariance) is a statistical model that combines both ANOVA (analysis of
161 variance) and linear regression. ANOVA tests the hypothesis that the groups of a dependent variable
162 are significantly different from a categorised independent variable, based on a given significance
163 level. When combining linear regression with ANOVA, the slopes of the groups of the dependent
164 variable can be tested to see whether they are collectively significantly different or not. Hence, by
165 using the F-test, ANCOVA tests the hypothesis that all groups are significantly different against the
166 null hypothesis that they are all the same. For comparisons between adjacent slopes, as opposed to
167 an overall test as in ANCOVA, a multiple comparison procedure is performed post-hoc ANCOVA.

168 With comparisons between three or more groups, simultaneous statistical inferences increase the
169 chances of falling into type I error. Multiple comparisons procedure avoids this by increasing the
170 threshold for inferences.

171 As an aside, least squares regression (which is conventionally used for determining scaling exponents
172 for DFA) and other statistical models adopted herein, are based on the assumption of independence
173 of residuals. However, this is not true when it comes to DFA data points due to the method of their
174 computation which involves an overlap of segments when determining $F(L)$ for the different time
175 scales.

177 Crossovers observed when analysing DFA results may either be indicative of a true difference in the
 178 scaling behaviour of the fluctuations or may be induced due to non-stationarities or periodicity
 179 inherent in the data (Kantelhardt, Koscielny-Bunde et al. 2001, Chen, Ivanov et al. 2002, Hu, Ivanov
 180 et al. 2001). (Kantelhardt, Koscielny-Bunde et al. 2001) have studied in detail the effects of a
 181 polynomial or oscillatory trend on DFA results and show that higher order DFA can, in many cases,
 182 help in determining true correlation of the fluctuations and the cause behind the occurrence of a
 183 crossover. This systematic handling of trends and periodicity gives DFA an advantage over other non-
 184 detrending methods (Kantelhardt, Koscielny-Bunde et al. 2001).

185 In previous studies researchers removed periodicity in a time series prior to DFA in order to
 186 determine ‘true scaling exponents’ ((Sadegh Movahed, Jafari et al. 2006, Li, Zhang 2007, Hu, Ivanov
 187 et al. 2001, Kavasseri, Nagarajan 2004)). In this study, periodicity is considered to be part of the
 188 fluctuation structure that is naturally induced by meteorological and hydrological processes, and
 189 hence will not be removed and instead will be identified in the fractal behaviour. In addition, since
 190 hydrological datasets are generally quasi-periodic, removal of periodicity inevitably leads to
 191 unintended modification or addition of trends or a smoothing of the fluctuations.

192 The scaling behaviour of a time series is approached asymptotically, hence high order DFA results
 193 deviate from a co-linear trend at smaller time scales and this affects the determined scaling
 194 exponent (Kantelhardt, Koscielny-Bunde et al. 2001). This deviation is overcome by dividing $F(L)$
 195 by a correction factor $K(s)$, which in turn is determined by averaging over configurations of
 196 surrogate datasets that are Monte-Carlo simulations of the original time series (100 configurations
 197 will be used in this study) to obtain a modified variance measure, $F_{\text{mod}}^{(n)}(L)$ (Kantelhardt, Koscielny-
 198 Bunde et al. 2001):

$$199 \quad F_{\text{mod}}^{(n)}(L) = \frac{F^{(n)}(L)}{K_{1/2}^{(n)}(L)} = F^{(n)}(L) \frac{\left\langle \left[F_{\text{shuff}}^{(n)}(L') \right]^2 \right\rangle^{1/2} L^{1/2}}{\left\langle \left[F_{\text{shuff}}^{(n)}(L) \right]^2 \right\rangle^{1/2} L'^{1/2}} \quad \text{for } L' \approx N/20 \quad (5)$$

200 Where $\langle \dots \rangle$ denotes the average over all configurations and $F^{(n)}(L)$ denotes the computed
 201 variance measure from step 4 using n^{th} order DFA, i.e. DFAn.

202 Figure 1 presents a flowchart, which summarises the r-DFAn procedure explained above.

203

204 *Illustration of r-DFAn*

205 Here r-DFAn involves performing r-DFA1 to r-DFA6 after which artificial deviations in fractal
 206 behaviour are resolved by using equation (5). The global scaling exponent is then determined for all
 207 DFA orders using robust regression with bi-square weighting. This is followed by determining
 208 crossovers (if any) using piecewise linear regression, the results of which are analysed using
 209 ANCOVA, and, in turn, the results from the ANCOVA are assessed using a multiple comparison
 210 procedure in order to ensure that the chosen number of crossovers are statistically significant. The
 211 code has been made available online in (Habib 2016).

212 A synthesized mono-fractal signal with specified scaling behaviour and crossover location is used to
 213 illustrate the r-DFAn method. The fractal signal is generated using Fourier analysis by scaling white
 214 noise in the frequency domain in order to produce a power spectral density that possesses a certain
 215 known scaling behaviour (Kantelhardt, Koscielny-Bunde et al. 2001). This is generated as follows:

- 216 1. Fourier transform a realisation of white noise from time domain ($u(t)$) to frequency domain
 217 ($u(f)$):

218
$$u(f) = \int_{-\infty}^{\infty} u(t) e^{-2\pi i t f} dt \quad (6)$$

- 219 2. Scale the obtained power spectral density according to the following equation:

220
$$F(f) = u(f) \times \left(\frac{f_{CO}}{f} \right)^{\frac{2\alpha-1}{2}} \quad (7)$$

221 Where f_{CO} is the frequency corresponding to crossover t_{CO} , and $\alpha = \begin{cases} \alpha_1 & \text{for } f \leq f_{CO} \\ \alpha_2 & \text{for } f > f_{CO} \end{cases}$.

- 222 3. Repeat steps (1) and (2) N times and compute the average power spectral density estimate:

223
$$F_{av}(f) = \langle F(f) \rangle_n \quad (8)$$

224 Where $\langle \dots \rangle_n$ is the average over n configurations.

- 225 4. Perform inverse Fourier transform on the computed average power spectral density to
 226 obtain a mono-fractal signal in the time domain with a crossover in the scaling regime:

227
$$F(t) = \int_{-\infty}^{\infty} F_{av}(f) e^{2\pi ift} df \quad (9)$$

228 $F(t)$ is obtained using 100 configurations of a series of length $2^{21} = 2,097,152$ data points, and
 229 with a crossover, in the time domain, at 500 time units and a scaling exponent of 1.0 and 0.5 before
 230 and after the crossover respectively (Figure 2). r-DFA is used to determine statistically significant
 231 scaling exponents of the synthesized signal and the results are presented in Figure 3.
 232 r-DFA produced results similar to that in Kantelhardt, Koscielny-Bunde et al. (2001) where the
 233 crossover locations lie ahead of the theoretical location and moves forward on the time scale axis
 234 with the increase in DFA order. The persistence of the crossover across all r-DFA orders indicates
 235 that there is a change in the scaling regime. The fluctuation structure of the series at all time scales is
 236 intertwined. This is evident from the determined scaling exponents where the segment that should
 237 possess a SE of exactly 1.0, exhibits a SE less than 1.0 and the segment that should possess a SE of
 238 exactly 0.5 tends to exhibit a SE higher than 0.5. This shows how the white noise segment and the
 239 rescaled structured noise segment inevitably affect each other, and in-turn, affect the location of the
 240 crossover.

241 The crossovers in Figure 3 are compared by plotting them against the respective DFA order (Figure
 242 4). Evidently, the crossover value progresses across DFA orders following a linear trend.

243 To the best of our knowledge, the following three publications introduced methods for objective
 244 fractal behaviour identification using DFA: (Echeverria, Rodriguez et al. 2016, Gulich, Zunino 2014,
 245 Grech, Mazur 2013). The most recent method (Echeverria, Rodriguez et al. 2016) identifies a
 246 transition range for the change in scaling behaviour rather than a point at which change occurs. The

247 second method uses the coefficient of determination (R^2) (Gulich, Zunino 2014) to determine non
248 overlapping segments with the best R^2 values. The different combinations of non-overlapping linear
249 segments are used to infer different scaling regions in the DFA results. The third method introduced
250 by (Grech, Mazur 2013) uses a similar methodology as in the Joinpoint Trend Analysis Software for
251 cancer research (National Cancer Institute 2016) where changes in trends are identified when the
252 probability distribution of the sum of residuals of a piecewise linear fit is significantly different from
253 a piecewise linear fit with one additional segment.

254 The novelty of the r-DFA method is that it explicitly determines the statistical significance of
255 adjacent scaling regimes while taking into account the total number of scaling regimes with the help
256 of the multiple comparison procedure as previously explained.

257

258 **Study site**

259 *Description*

260 The study area is located in Wallingford, Oxfordshire, United Kingdom (Figure 5) with a number of
261 gauges installed on the site of the Centre for Ecology and Hydrology (CEH). The Wallingford
262 Observatory comprises two shallow boreholes (WL84 and WL85) screened within shallow alluvial
263 gravel deposits, a stilling well located in the nearby River Thames, and an automatic weather station
264 (AWS). Their locations are shown in Figure 5. The boreholes are sited on a grass verge adjacent to a
265 set of buildings at CEH. The verge is actively managed and cut frequently during the growing season.
266 Several poplar trees (*Populus*) and a sycamore tree (*Acer pseudoplatanus*) are located within 10 m of
267 the borehole. Areas of hard standing, associated with nearby buildings and car parks, limit
268 infiltration at the site. The stilling well is positioned 420 m west of the boreholes and is adjacent to
269 the eastern bank of the River Thames. The AWS lies between the boreholes and stilling well, within
270 cattle pasture.

271 *Geology and hydrogeology*

272 The Wallingford site is located close to a major geological boundary in the course of the River
273 Thames. Upstream from Wallingford, the river flows across a broad, mudstone-floored valley formed
274 from Early Cretaceous Gault Clay (Figure 6). Downstream from Wallingford, the River Thames is
275 progressively constricted as it passes through the Goring Gap which divides the Chiltern Hills and the
276 Berkshire Downs. Here the River Thames flows across the Upper Greensand and the overlying Late
277 Cretaceous Chalk Group. The geological formations are inclined gently toward the southeast so that
278 the river crosses younger formations in a downstream direction.

279 The Upper Greensand in the Wallingford area is a heterogeneous deposit of mudstones, sandstones
280 and siliceous malmstones and forms an aquifer unit approximately 25 m thick above the Gault Clay
281 (Figure 6). The Upper Greensand is overlain by the West Melbury Marly Chalk, which although
282 forming the base of the Chalk Group, differs markedly from the pure-white, high-porosity
283 carbonates, which form the bulk of the overlying Chalk. The West Melbury Marly Chalk is largely
284 composed of carbonate-rich mudstone (marl) with a distinctive glauconite-rich unit (Glauconitic Marl
285 Member) at the base. This basal part of the Chalk has a low permeability and springs are often seen
286 to emerge from overlying thick-bedded chinks around the flanks of the Chiltern Hills and Berkshire
287 Downs. The spring line is generally located just below the boundary with the overlying Zig Zag Chalk
288 Formation.

289 The River Thames is separated from the Cretaceous bedrock formations by a layer of Quaternary
290 sand and gravel, which is typically around 5 m thick and can extend across the valley floor for up to
291 2 km. The sands and gravels are subdivided into a number of named river terrace deposits. The
292 Northmoor Sand and Gravel member occurs beneath and adjacent to the floodplain of the modern
293 River Thames and in the Wallingford area is subdivided into a lower facet and an upper facet. The
294 lower facet is generally concealed beneath a thin (metre-thick) cover of Holocene alluvium.

295 The Wallingford boreholes were drilled into the upper facet of the Northmoor Sand and Gravel on a
296 minor terrace just above the level of the modern Thames floodplain. They proved 0.5 m of soil,
297 overlying 4.0-4.2 m of interbedded sandy gravel and gravelly sand with fine to coarse pebbles

298 composed largely of limestone, ironstone and flint. The gravels rest sharply on grey mudstones of
299 the Glauconitic Marl. This low permeability horizon at the base of the Chalk Group hydraulically
300 isolates the highly permeable sands and gravels from the underlying Upper Greensand aquifer.
301 There is a hydraulic head difference of around 4 - 5 m between this aquifer and the overlying terrace
302 sand and gravels, with the potentiometric head of the Upper Greensand typically above ground level
303 during the winter.

304 *Hydrology*

305 The River Thames is the most prominent surface water feature traversing the sands and gravels with
306 a mean flow and baseflow index (BFI) of 28.3 m³/s and 0.64, respectively, as monitored 8 km
307 upstream at Day's Weir (Marsh, Hannaford 2008). The River Thame is the most significant local
308 tributary of the Thames, with the confluence 6.5 km upstream of the site. The Thame has a mean
309 flow of 3.8 m³/s and BFI of 0.59 at Wheatley (51.740° N 1.115° W). Ewelme Brook is an example of
310 one of the smaller groundwater dominated streams seen locally which emerge as springs from the
311 top units of the West Melbury Chalk, and flow across the sands and gravels before converging with
312 the Thames. It has a mean flow and BFI of 0.05 m³/s and 0.98, respectively, 400 m downstream of its
313 source (51.620° N 1.074° W). The mean annual rainfall recorded between 1972 and 2007 in
314 Wallingford is 596 mm.

315

316 **Data Collection and Inspection**

317 *Data Collection*

318 The six datasets discussed herein are river stage, groundwater levels, river temperature,
319 groundwater temperature, rainfall and air temperature. Details of the datasets and gauge
320 installation are summarised in Table 1 and Table 2 respectively.

321 Groundwater levels and temperature are monitored using a 3.5 mH₂O range MEAS KPSI™ 501
322 pressure transducer in borehole WL84. The sensors are located 4.5 m below ground level adjacent to
323 the screen for representative groundwater temperature measurements. (Sorensen, Butcher 2011)

324 reported this was the most accurate pressure transducer (Transducer F) out of sixteen models tested
325 with an accuracy in field tests of ± 4 mm and no evidence of drift. An additional 3.5 mH₂O range
326 MEAS KPSI™ 500 pressure transducer is also installed within the borehole to validate the primary
327 dataset. Temperature on both KPSI™ sensors is typically accurate to $\pm 0.1^\circ\text{C}$, but specified to within
328 $\pm 0.25^\circ\text{C}$. All measurements are recorded every minute and telemetered using Adcon A723 addITs.
329 In borehole WL85, a 3.5 m range In-Situ Inc. Level TROLL® 500 is installed and logging at a 1 minute
330 frequency. This sensor is specified as accurate to ± 3.5 mm by the manufacturer. This dataset
331 provides a backup dataset in the event of transducer or telemetry failure at borehole WL84.
332 Frequent manual observations of groundwater level are undertaken at both boreholes with a dip
333 tape to detect any evidence of instrument malfunctioning or drift (Post, Asmuth 2013). The dip tape
334 is regularly calibrated against an EU Class I measuring tape, which has a tolerance of ± 0.4 mm over
335 the length used.
336 At the stilling well, river stage and temperature were measured at 1 minute interval with a 3.5 mH₂O
337 range MEAS KPSI™ 500. There is currently no backup sensor installed at this location.
338 Meteorological variables are monitored every 15 minutes using a Didcot AWS, with DICO Probes for
339 air temperature. The temperature is typically accurate to $\pm 0.1^\circ\text{C}$, although calibrated to an accuracy
340 of $\pm 0.2^\circ\text{C}$. Rainfall is monitored with a tipping bucket rain gauge (0.2mm tip volume), which is
341 mounted at ground level to reduce the effects of undercatch (Rodda and Dixon, 2012).

342 *Data quality control*

343 The groundwater and river datasets span 2,101,873 records from 08:48 2nd January 2012 until 00:00
344 01st January 2016. These datasets contained missing values, which totalled 1.0 and 0.7 % of the total
345 record lengths in the borehole and stilling well, respectively. These were infilled using four
346 techniques (Table 3). The datasets contained several small gaps (<10 min), including numerous
347 1 minute gaps, for example the groundwater level dataset contains 393 records. These records were
348 all infilled via linear interpolation, which is considered reasonable over such short timeframes.

349 The majority of groundwater level data infilling was via linear regression with borehole WL85
350 ($R^2 = 1.00$ from 616482 concurrent records). However, over 33 hours in June 2013 there was no
351 corresponding record from WL85. Therefore, the rate of change over the preceding 24 hour period
352 was used to reconstruct the groundwater level data. This enabled anticipated short-term
353 fluctuations to be captured in the absence of any precipitation. This was not thought to have a
354 significant impact on the results, as the infilled time is less than 0.25% of the entire time period.
355 Linear interpolation over periods in excess of 10 minutes was used for the groundwater temperature
356 and river datasets.

357 There was no evidence of drift noted in the WL84 groundwater level dataset. This was confirmed via
358 comparison with manual level observations which showed no deterioration in accuracy with time,
359 with all data within ± 3 mm. Furthermore, there was no systematic deviation in readings between
360 the pressure transducers within borehole WL84.

361 Both air temperature and rainfall datasets contained missing values totalling 10% in record length,
362 notably 3516 records between 13th November and 20th December 2013 and 4700 records between
363 24th December 2014 and 11th February 2015. These were infilled with hourly data from Benson
364 located 2 km northeast of Wallingford and is indicated in Figure 5. Benson temperature data were
365 downsampled to 15 minute using linear interpolation, then used to infill the Wallingford data. Rainfall
366 data were not downsampled, and were not adjusted for location as 88 % of the concurrent hourly
367 totals were identical.

368 *Data Inspection: Processes and time-scales*

369 Rainfall was highly unusual during the study period, exceeding the average in 2012 and 2014 by
370 about 40 and 50% respectively, and approximately equal to the average in 2013 and 2015 by about 3
371 and -5% respectively. However, during early 2012 Southern Britain had actually been experiencing
372 drought conditions. In April, though, there was an abrupt change in the weather pattern across the
373 UK, which preceded unprecedented rainfall locally (Parry, Marsh et al. 2013). This resulted in
374 atypical river flows during late spring and summer and, moreover, inhibited the development of soil

375 moisture deficits during summer 2012. Consequently, the onset of runoff was rapid during the
376 winter rains causing periods of high flow throughout October 2012 – April 2013 along the Thames.
377 The summer of 2013 was reasonably warm and dry and resulted in high soil moisture deficits
378 developing. However, the clustering of deep depressions throughout December 2013 and January
379 2014 produced high rainfall, high runoff and the highest average January flow along the Thames
380 since records began in 1883 (CEH/Met Office, 2014).

381 Groundwater head remains elevated above the river stage throughout the period indicating the
382 potential for perennial groundwater discharge to the Thames (Figure 7). The elevated groundwater
383 head could be supported through upwelling from the Chalk to the East or the Upper Greensand to
384 the West where the overlying Glauconitic Marl Member is absent. Other contributions could
385 originate via losses from upgradient surface waters, such as the River Thame or more groundwater
386 dominated streams like Ewelme Brook.

387 Rises in River Thames stage are a response to flow from upstream catchments and hence are much
388 greater than concomitant rises in groundwater head (Figure 7). The River Thames response would be
389 a combination of both groundwater discharge and overland flow which is likely to occur north of the
390 piezometer site, where the river and its tributaries flow across the impermeable Gault Clay
391 Formation.

392 Groundwater temperature is relatively stable displaying a low-amplitude sinusoidal pattern which
393 peaks in October and reaches its minima in April (Figure 7). These peaks and troughs are lagged in
394 comparison to air temperature. By contrast, river temperature responds quickly to air temperature
395 throughout, but without the same extremes because of the higher thermal capacity of water.

396 It is observed that there can be a marked and rapid rise in borehole water level during and shortly
397 after intense rainfall events (Figure 8 and Figure 9). This is believed to be due to the Lisse effect,
398 which arises from air entrapment during these events, particularly during summer. Figure 9 shows
399 the response of the borehole water level to individual rainfall events during August (a summer
400 month) where the Lisse effect is clearly observed and during November-December (winter months)

401 where the Lisse effect is less prominent. The Lisse effect tends to occur in shallow unconfined
402 riparian aquifers similar to the that studied here (Weeks 2002). During these changes in level there
403 are also concurrent changes in groundwater temperature (Figure 9). Figure 9 captures one such
404 event. Initial change in groundwater temperature (marked as 'local minimum' in Figure 9) is
405 attributed to initial inflow of groundwater with a slightly different ambient temperature into that in
406 the well during the initial rise in the borehole water column. This is followed by a reversal in the
407 temperature gradient which occurs due to mixing of the water column in the well. The mixing is
408 believed to be induced by turbulence due to the rapid inflow and then outflow of water as a result of
409 the build-up and then reduction of air pressure in the unsaturated soil during the Lisse effect. This
410 results in a local temperature maximum occurring during the declining phase in the borehole water
411 level. The temperature then starts to transition into a new equilibrium state after the dissipation of
412 the Lisse effect. When such events occur during the winter an inverse response occurs with an initial
413 local maximum followed by a larger local minimum. The observed rise in groundwater level in Figure
414 9 is ~0.15 m in response to a rain event that had a cumulative depth of ~0.01 m. With a specific
415 yield estimate of about 0.15 for the study site, the observed rise in groundwater level is expected
416 not to exceed 0.07 m. And hence the 0.15 m rise in groundwater level for this event is evidently
417 caused by the Lisse effect.

418 Controls on river and groundwater levels are diurnal and seasonal. During the summer, river levels in
419 the stilling well are noticeably influenced by bow waves emanating from passing boat traffic. This
420 can result in random noise of several millimetres during daylight hours (Figure 8a). Such noise is less
421 pronounced during the winter months, and also tends to be focussed during weekends or public
422 holidays.

423 Evapotranspiration from groundwater storage is similarly diurnal and seasonal producing daytime
424 drawdown and overnight recovery typically between April and October (Figure 10). It is likely to be a
425 consequence of the nearby poplar trees which have been observed to root to at least 3.2 m below
426 the surface (Heilman, Ekuan et al. 1994) and could, therefore, tap the saturated zone directly.

427 Contributions from the sycamore are likely to be more limited as the species tends to restrict root
428 growth to within the top metre (Heilman, Norby 1998, Simon, Collison 2002).

429

430 **Results and discussion**

431 The Lisse effect – which was explained under the Data Inspection Section – is an artefact of the
432 monitoring well’s response to heavy rainfall events and is not, therefore, indicative of a physical
433 increase in groundwater storage. Hence, as suggested by (Zhang, Gong et al. 2011) the data will be
434 corrected for the Lisse effect. The procedure developed for the removal of the Lisse effect is detailed
435 in Appendix A. Both groundwater level and temperature data will be corrected for the Lisse effect
436 and fractal behaviour for both observed and corrected time series will be presented.

437 Figure 11 to Figure 14 Figure 14 present the results of r-DFAn for all the datasets listed in Table 1.

438 Table 4 presents a summary of the global scaling exponents and persistent crossovers in r-DFA1 for
439 all datasets.

440 The Lisse effect has a noticeable effect on the mono-fractal behaviour of groundwater temperature
441 and levels (Figure 11 and Figure 12), particularly at intermediate time scales (i.e. around 1000 mins
442 or 0.7 days). Where, in the case of the borehole water level, correction for the Lisse effect removes a
443 crossover, due to the reduction in $F(L)$, at these intermediate time scales. The global fractal
444 exponents for groundwater temperature with and without the Lisse effect are ~ 1.43 and ~ 1.40
445 respectively, and that for groundwater levels are ~ 1.68 and ~ 1.78 respectively. Hence, the global
446 scaling behaviour is not strongly affected by the existence of the Lisse effect.

447 Global fractal behaviour of rainfall, river stage and groundwater level (corrected for Lisse effect) at
448 the Wallingford site are consistent with previous studies (Matsoukas, Islam et al. 2000, Li, Zhang
449 2007) where rainfall is similar to white noise ($\alpha = 0.5$) and river stage and groundwater fluctuation is
450 more structured and tends to Brown noise ($\alpha = 1.5$). Here, the global scaling exponent for rainfall,
451 river stage and groundwater level are ~ 0.72 , ~ 1.60 and ~ 1.78 respectively (Figure 13-E, Figure 13-F
452 and Figure 13-G). (Little, Bloomfield 2010, Li, Zhang 2007, Zhang, Schilling 2004) speculate on the

453 role of runoff, recharge and the carrying medium i.e. soil, on altering the fluctuation structure of
454 rainfall to produce more structured fluctuation in groundwater level and river stage.

455 Crossovers are observed in all datasets studied. Notable is the protuberant shape observed for air
456 temperature (Figure 13-A), groundwater temperature (Figure 13-C), and river temperature (Figure
457 13-D) with maximum bulge for r-DFA1 at around ~ 14 hours, ~ 11 hours and ~ 9 hours respectively.

458 Persistence of this crossover across higher order r-DFA n indicates a strong presence of a periodic
459 cycle with a cycle length smaller than that observed in r-DFA1 at the maximum bulge (Li, Zhang
460 2007, Sadegh Movahed, Jafari et al. 2006, Kantelhardt, Koscielny-Bunde et al. 2001). The degree of
461 protuberance in the fractal domain is proportional to the amplitude of the cycle in the time domain
462 (which is presented in Figure 4). The amplitude of the cycle in Figure 4 is related to the degree of
463 protuberance in that the degree of protuberance for air temperature is larger than that for river
464 temperature and which in turn is larger than that for groundwater temperature.

465 An important speculation that relates the r-DFA n results of the three temperature time series and
466 the three hydrological time series (i.e. rainfall, groundwater levels and river stage) is the degree of
467 similarity of the DFA results of the former compared to that of the latter. The similarity of r-DFA
468 results of the three temperature time series (i.e. air temperature, river temperature and
469 groundwater temperature), is attributed to the underlying dominantly-linear heat transfer process
470 that does not induce or alter the fractal properties of the temperature time series. However, the
471 DFA results of rainfall, river stage and groundwater levels do not exhibit the same degree of
472 similarity due to underlying non-linear recharge, runoff and baseflow transfer functions.

473 The rainfall series has one persistent crossover at 1.6 days for r-DFA1. Investigation of the rainfall
474 series in the time domain revealed that all storms last for a maximum period of 1.4 days and about
475 75% of dry period length (i.e. dry periods between storms) are shorter than 1.6 days; Storms were
476 estimated by clustering non-zero rain with no longer than 2 hours of dry period as was done in
477 (Ireson, Butler 2011)). Keeping these estimates in mind, it is speculated that the 1.6 days crossover
478 separates between two regimes where the first regime, that corresponds to scales smaller than 1.6

479 days, is affected by the intermittency of rainfall. The second regime, that corresponds to scales from
480 1.6 days to a number of months, is no longer dominated by the effect of storms and rain events.
481 Published results for rainfall do not coincide with the rainfall series at Wallingford. One such case are
482 the rainfall series studied in (Matsoukas, Islam et al. 2000) from 9 different locations in the US. A
483 crossover between 5 and 10 days was observed at the 9 locations and its occurrence was related to
484 the separation between meteorological and climatological regimes that act as forcing on the rainfall
485 time series. However, the scaling exponents before and after the crossover coincide with our
486 findings where a SE of about 1.0 is observed at smaller scales and a SE of about 0.6 is observed at
487 larger scales. In another publication, (Tessier, Lovejoy et al. 1996) observed a crossover at about 16
488 days for rainfall time series collected from 30 different catchments in France. (Koscielny-Bunde,
489 Kantelhardt et al. 2006) studied daily rainfall data from various places across the world, hence, it is
490 only the scaling exponents on larger scales that can be compared. The scaling exponents from
491 Wallingford and those reported in (Koscielny-Bunde, Kantelhardt et al. 2006) are similar because
492 both are close to white noise as opposed to $1/f$ noise that is exhibited across smaller scales in the
493 Wallingford 15-minute rainfall data.

494 The fractal behaviour of river stage (Figure 13-F) and groundwater levels (Figure 13-G) are very
495 similar. (Li, Zhang 2007) speculated the effect that river stage fractal properties would have on that
496 of groundwater levels, especially at the larger scales. However, River Thames, which is generally
497 groundwater dominated (with a BFI of 0.64 measured 8 km upstream of the site), is expected to
498 have fractal properties similar to that of groundwater fluctuation.

499 (Little, Bloomfield 2010), as reported in (Labat, Masbou et al. 2011), studied GW levels and found
500 that they exhibited scaling exponents ranging from 1.20 to 1.65. (Li, Zhang 2007) reported two
501 crossovers; one between a few days and 10 days and the second was between a few months and a
502 year. Unfortunately, the groundwater scale ranges studied herein are different from those studied in
503 (Li, Zhang 2007), hence a comparison is not possible. However, according to (Yu, Ghasemizadeh et al.

504 2016), the fractal behaviour of groundwater levels is found to be site specific and hence need not be
505 similar.

506 Finally, Figure 14 summarises all crossovers that persist across all r-DFA orders in the 6 datasets
507 studied. As explained earlier when illustrating r-DFA on the synthetic signal, due to anticipated
508 interaction between the different scaling regimes, the 'true' crossover is expected to fall before the
509 crossover in r-DFA1. Evidently, the crossovers in all datasets (except for the second CO in the
510 groundwater levels dataset) follow a generally linear trend. Noteworthy is the similarity of slopes of
511 the three unaltered temperature time series (air temperature, river temperature and groundwater
512 temperature) that the crossovers follow. In addition, the slopes for river stage and the first CO of
513 groundwater levels are of similar magnitude.

514

515 **Summary and conclusions**

516 The fractal behavior of six very high-resolution datasets was investigated using robust detrended
517 fluctuation analysis procedure (r-DFA) that allows for accurate non-subjective determination of
518 global scaling exponents and statistically significant changes in the scaling regimes (crossovers). The
519 datasets investigated were 1-minute river and groundwater temperature and levels, 15-minute
520 rainfall and temperature. The variables were collected in Wallingford, UK, over a period of 4 years.

521 The study site is formed of a shallow gravel aquifer that drains into River Thames. Detailed
522 inspection of all variables in the time domain was presented along with their fractal behavior.

523 Due to the very high resolution of the data collected and the high permeability of the aquifer, the
524 Lisse effect was identified. Insights into the dynamics taking place inside the groundwater
525 monitoring well were inferred from a combined inspection of the one-minute groundwater level and
526 groundwater temperature data. Plant root uptake was clearly identified in the groundwater level
527 time series with recession during the day and infiltration during the night. The removal of the Lisse
528 effect from the affected time series showed how the Lisse effect influences the fractal behavior of
529 these time series at intermediate time scales (at about one day).

530 The high resolution of the data enabled the study of their mono-fractal behavior from a time scale as
531 short as 3 minutes for 1-minute river and groundwater data and a time scale of 45 minutes for the
532 15-minute meteorological data. At these scales, the river stage and groundwater levels exhibit a
533 strong and persistent crossover at sub-hourly time scales which would not be detected with coarser-
534 resolution time series.

535 As for the temperature time series, the periodicity, which is observed in the time series of the air,
536 river and groundwater temperature series, was clearly captured in the fractal analysis in the form of
537 a protuberant shape with a size proportional to the amplitude of the periodicity observed in the
538 time domain. We believe that the underlying (dominantly) linear process of temperature
539 conductance has led to an 'approximately linear' transfer of fractal behavior between the
540 temperature series whereas the underlying non-linear transfer processes of runoff and infiltration
541 that rainfall undergoes did not lead to the same degree of similarity in fractal behavior of rainfall,
542 river stage and groundwater fluctuation.

543 The fractal behaviour of all datasets was presented, however, a model is required in order to be able
544 to ascertain the driving forces that cause the observed fractal behaviour. The role of soil in acting as
545 a 'fractal filter' of water along its path way, and the role of the processes of recharge and base flow
546 on the fractal properties of rainfall, is a concept that, to the best of our knowledge, is not yet well
547 established. The degree to which models are able to capture fractal behavior of hydrological and
548 hydro-geological time series is an area worth investigation, in light of recent successful attempts like
549 that of (Williams, Pelletier 2015) and (Russian, Dentz et al. 2013).

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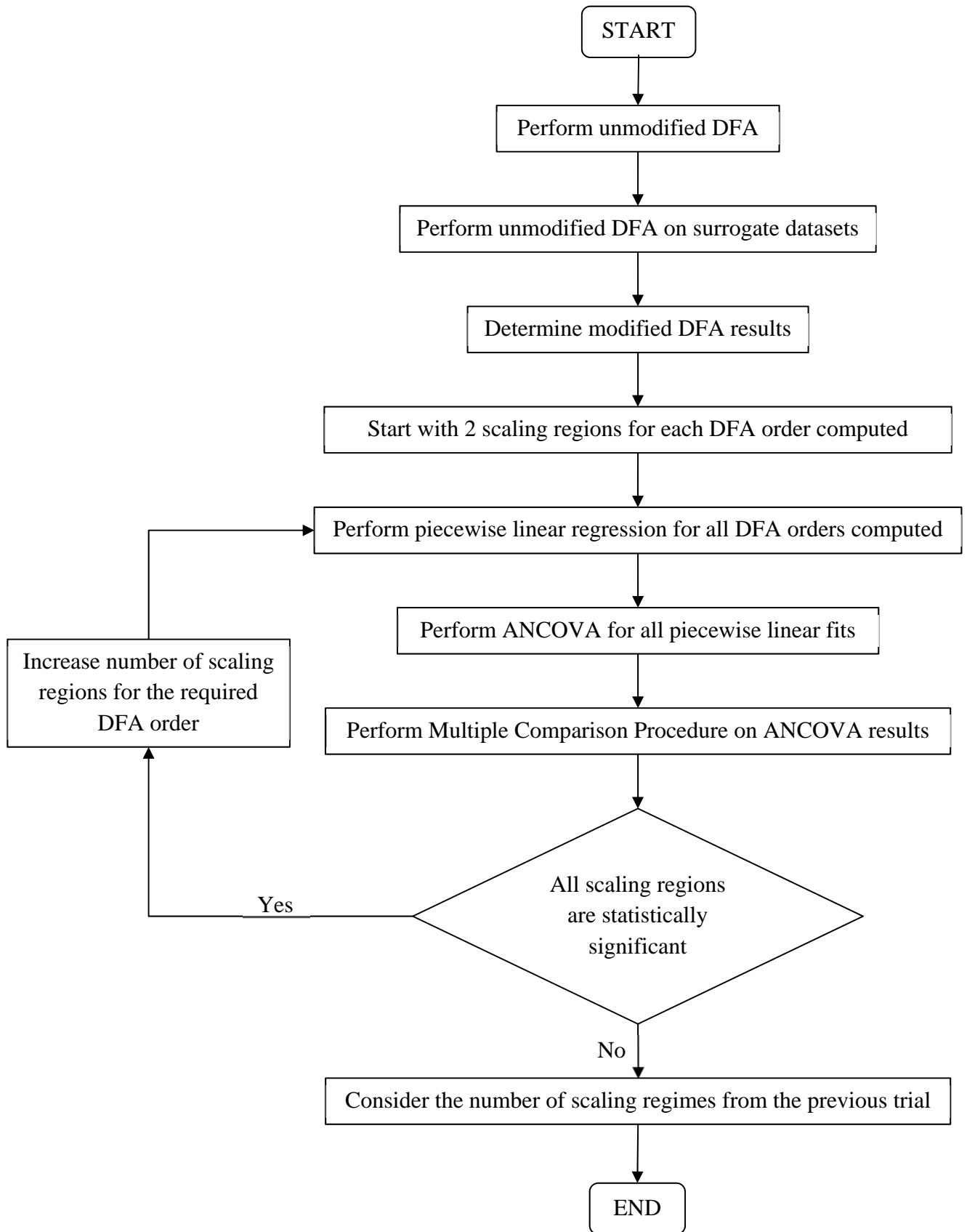
551 **Acknowledgment**

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554 James Sorensen, Dr John P Bloomfield, and Dr Andrew J Newell publish with the permission of the
555 Executive Director of the British Geological Survey (NERC).

556

557 **Figures and Tables**



558

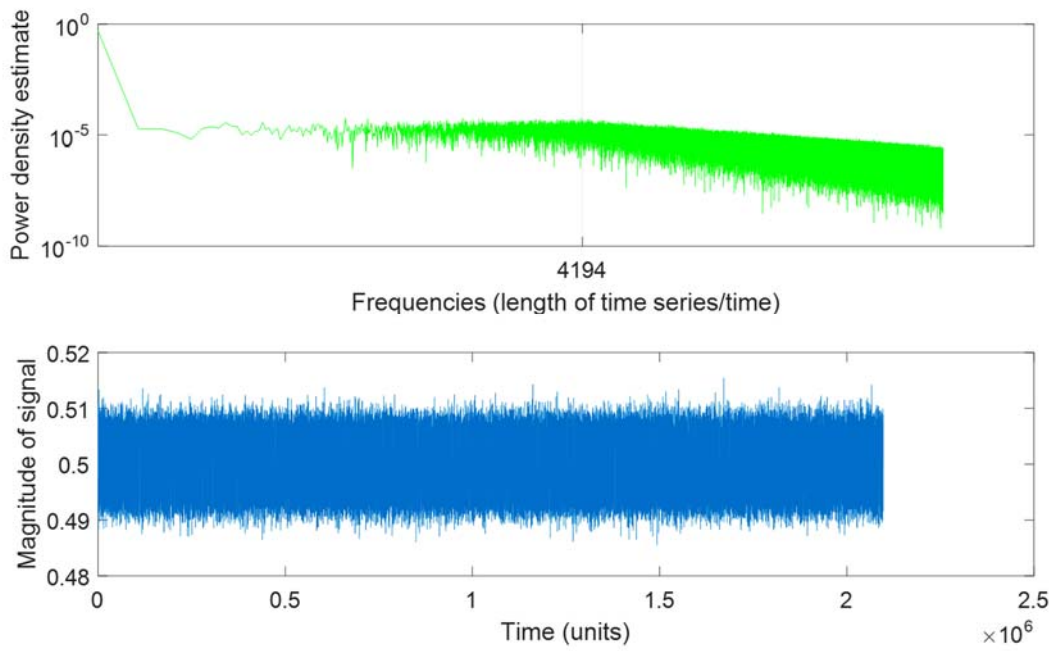
559 Figure 1 Flowchart of r-DFA procedure

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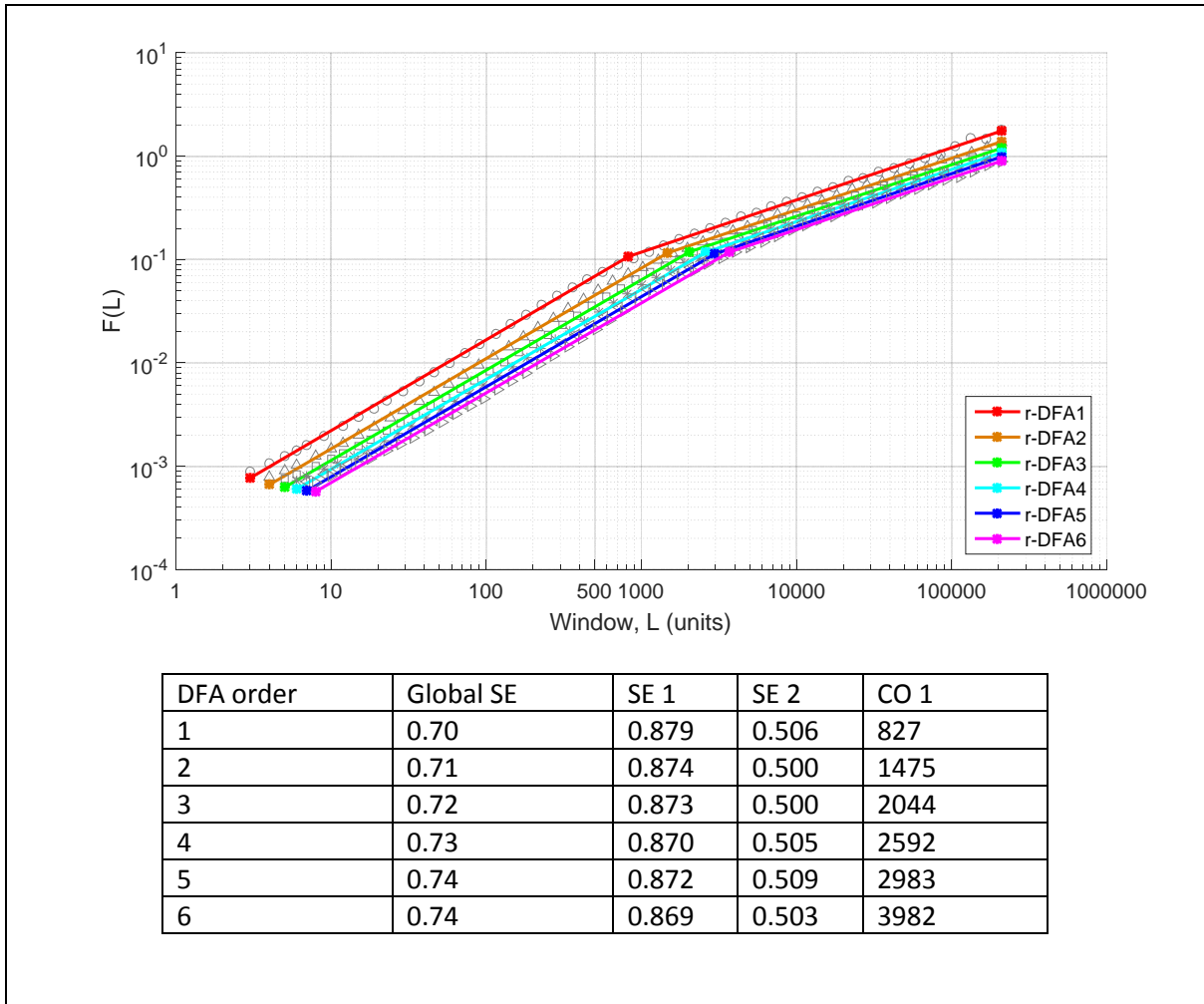


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565 Figure 2 Mono-Fractal signal in frequency (top panel) and time (bottom panel) domains with change in the
566 scaling regime at a frequency corresponding to 500 units (indicated with a grey line).

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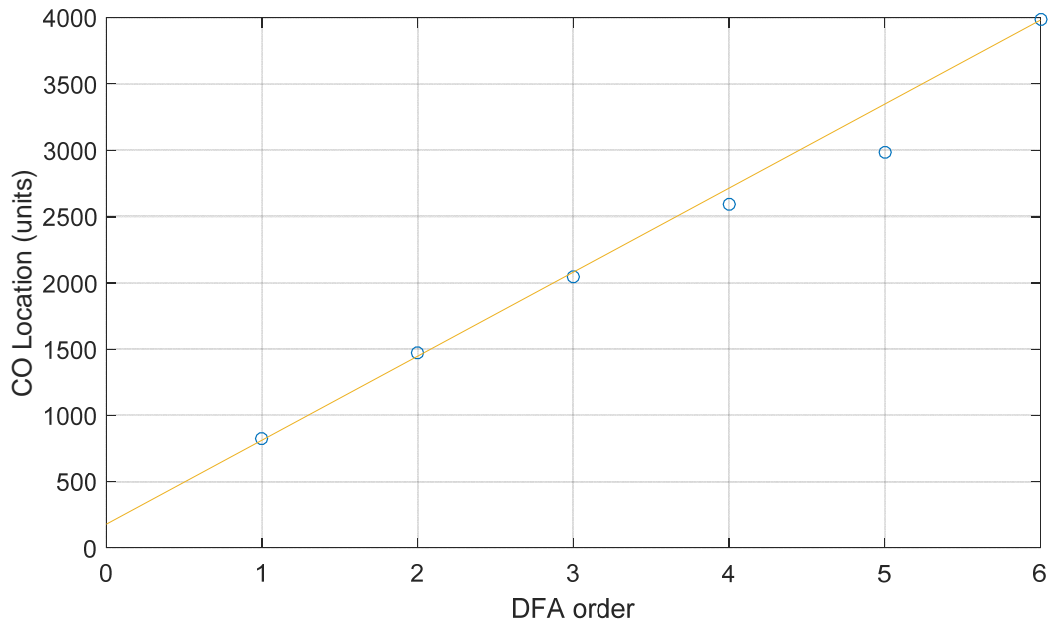
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570 Figure 3 r-DFA of synthesized mono-Fractal time series of length 221 data points, a theoretical crossover at
 571 500 units and a theoretical scaling exponent of 1.0 before crossover and 0.5 after the crossover.

572



573

574 Figure 4 Summary of COs of the synthetic mono-fractal signal with change in scaling regime

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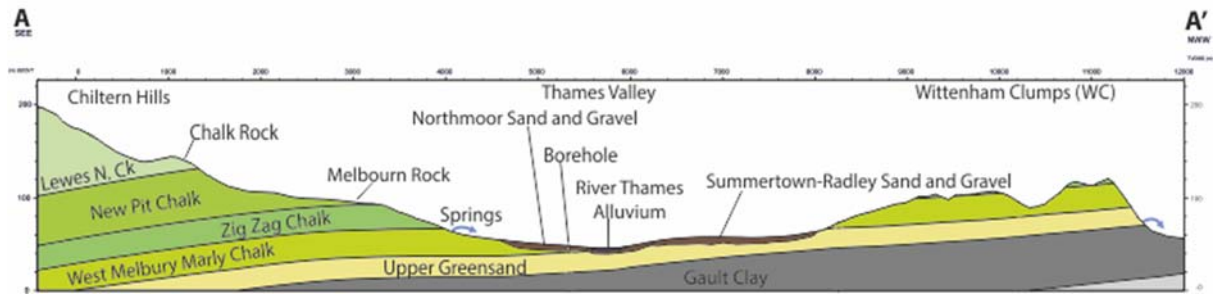
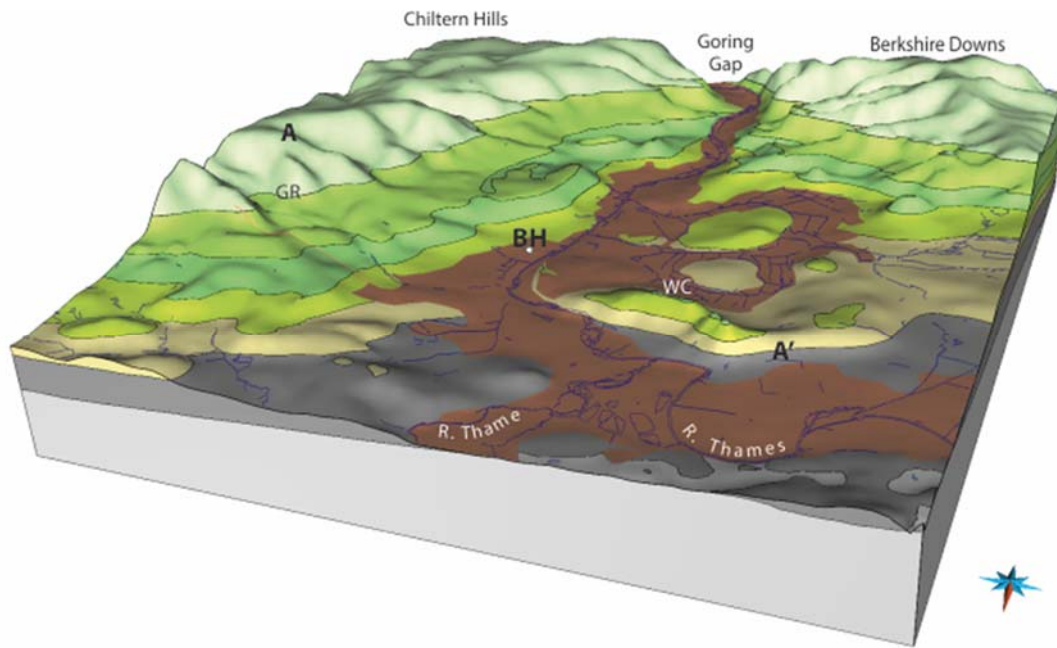
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578 Figure 5 Illustration of Wallingford study site location and relevant gauges from Google Earth

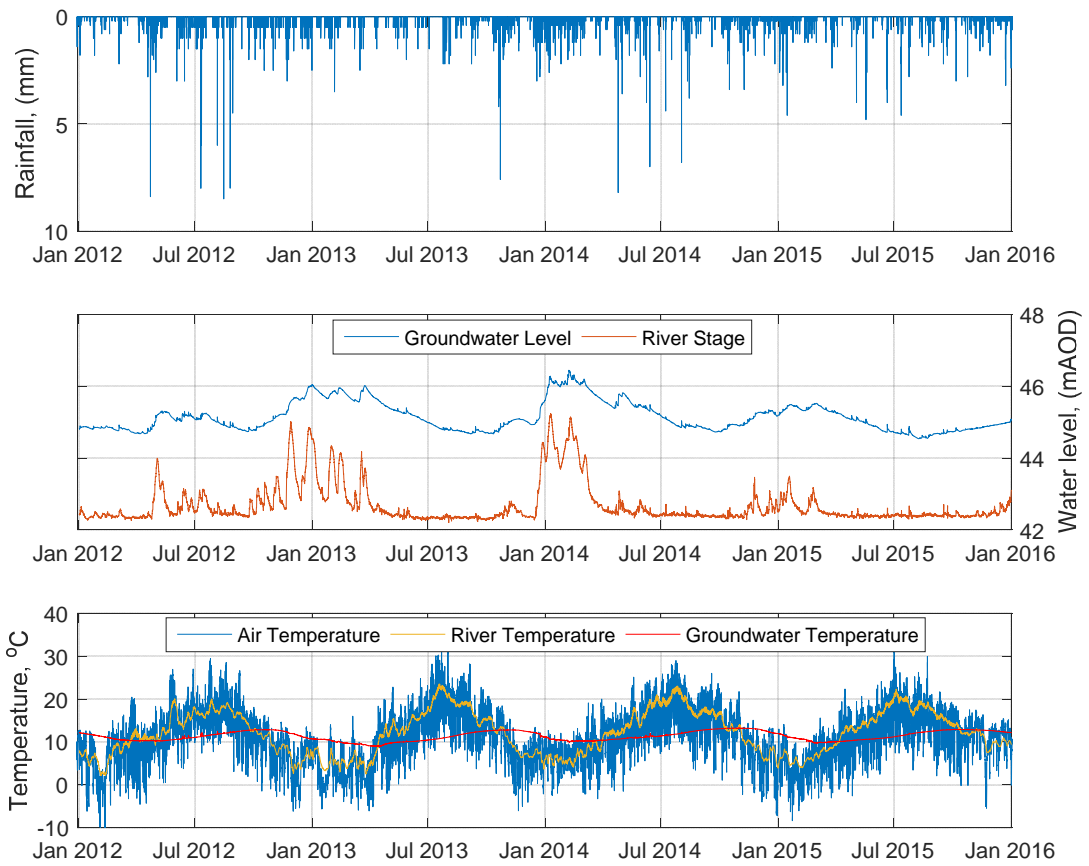
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580

581 Figure 6 Block diagram showing the topography and geology surrounding the borehole site. Block covers an area of approximately 16x17 km and is viewed looking south (downstream) toward the Goring Gap. The block
 582 covers an altitudinal range of 360 m and is viewed with a vertical exaggeration factor of X10. See cross-section
 583 (b) for a key to the colours of the geological formations and abbreviations.
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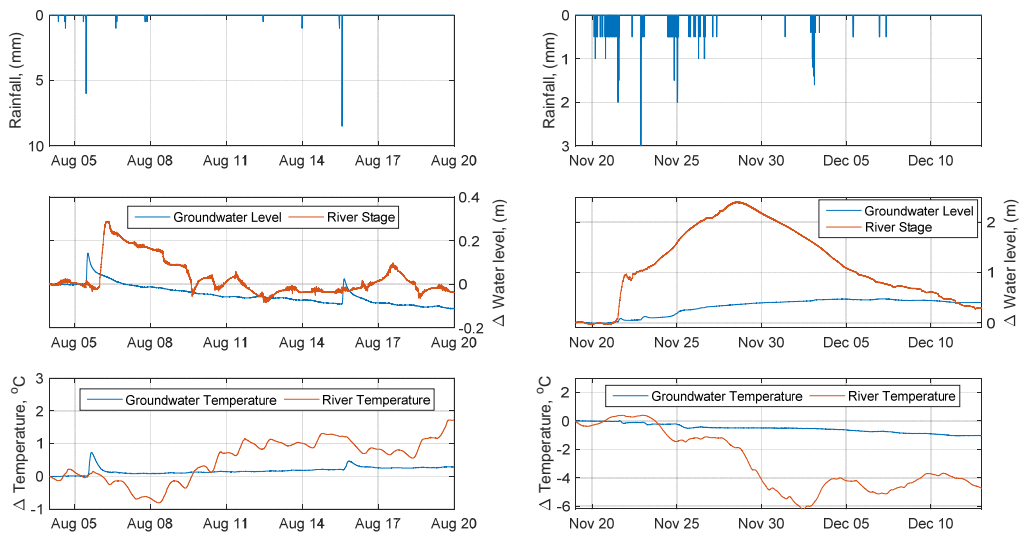
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587 Figure 7 Full time series of daily rainfall, river and groundwater level, and air, river and groundwater
 588 temperature.

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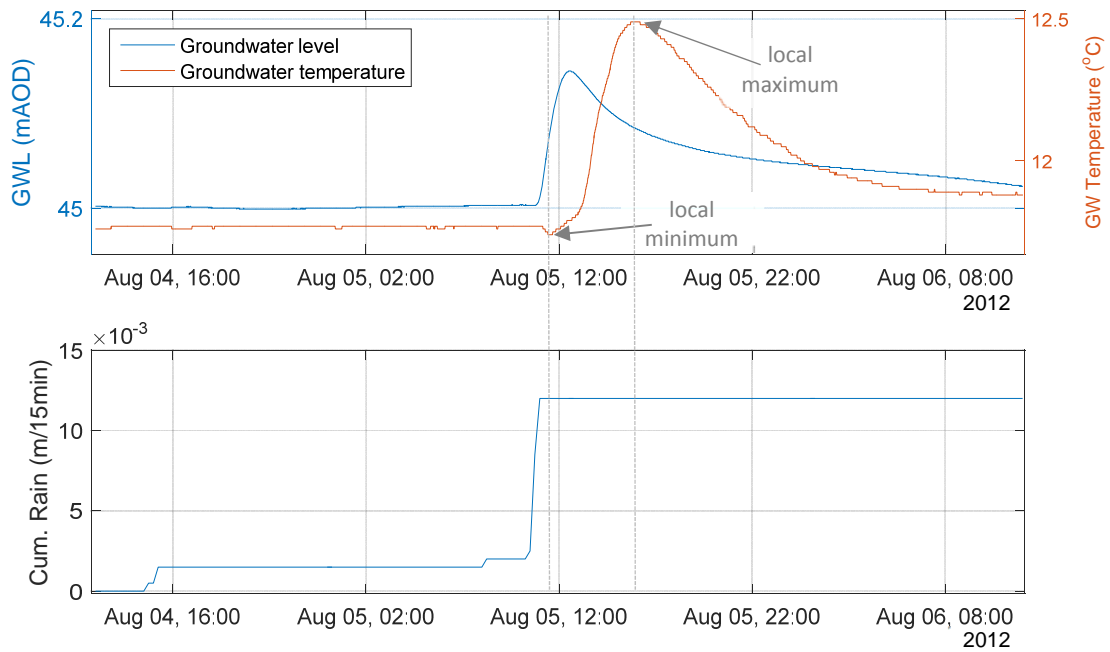


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591 Figure 8 Response of river and groundwater levels and temperature to events in (a) Left panel: August 2012

592 (b) Right panel: November 2012

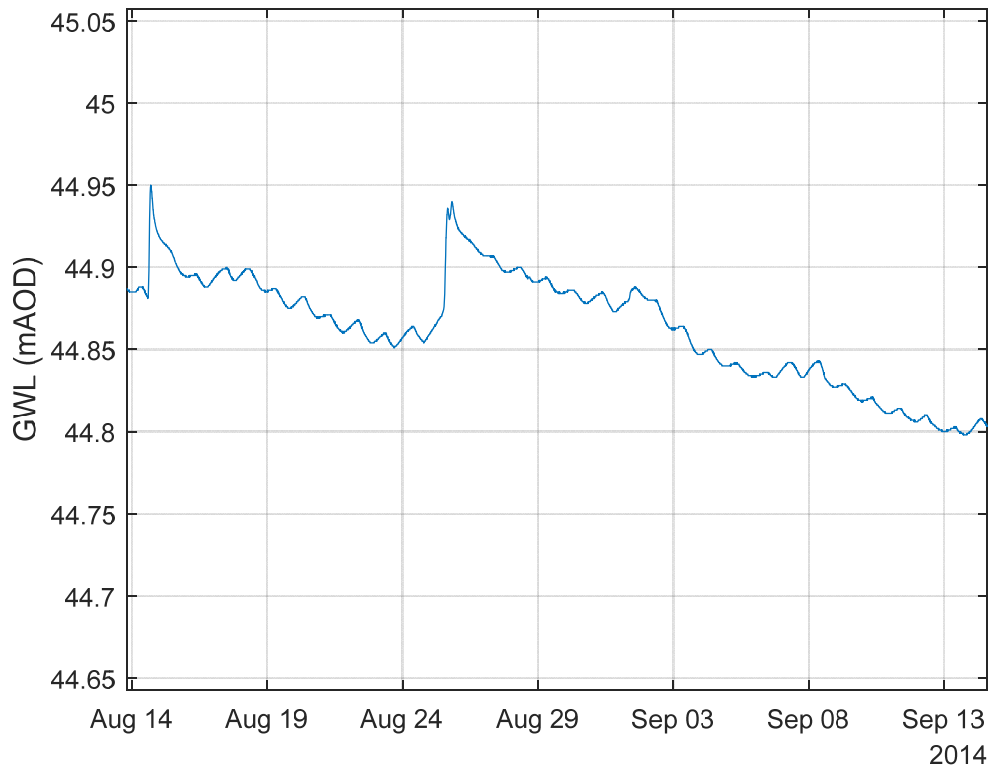
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595 Figure 9 Top panel: Groundwater level and temperature with focus on one Lisse event (grey dotted lines mark
596 minimum and maximum groundwater temperature differences); Bottom Panel: Coinciding cumulative rainfall.

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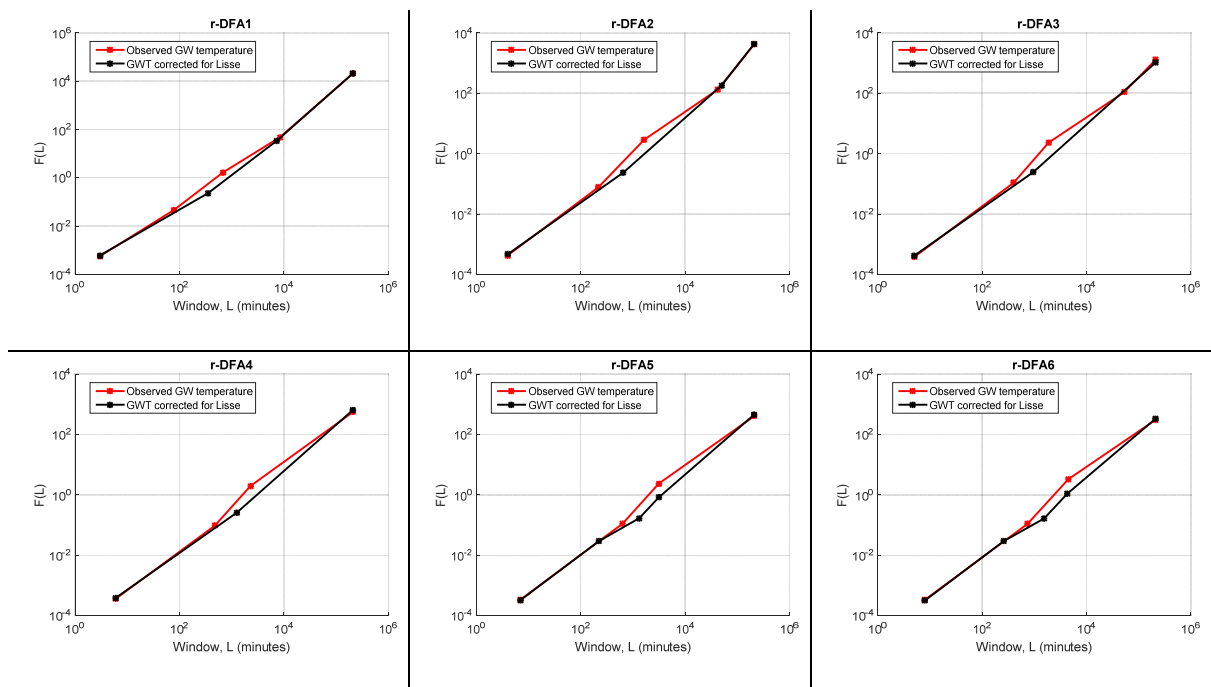


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599 Figure 10 Groundwater level at Wallingford exhibiting diurnal fluctuation due to plant root uptake during
600 daytime

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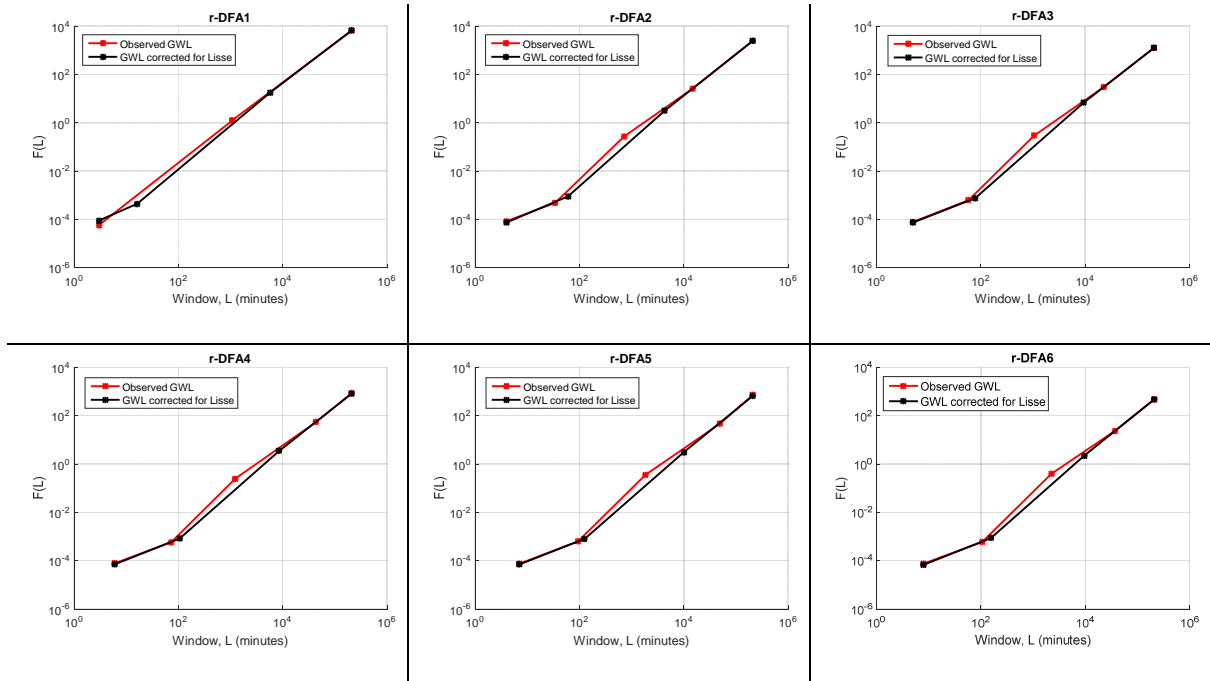


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604 Figure 11 Illustration of the effect of the Lisse effect on the fractal behaviour of Groundwater temperature

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608 Figure 12 Illustration of the effect of the Lisse effect on the fractal behaviour of Groundwater level

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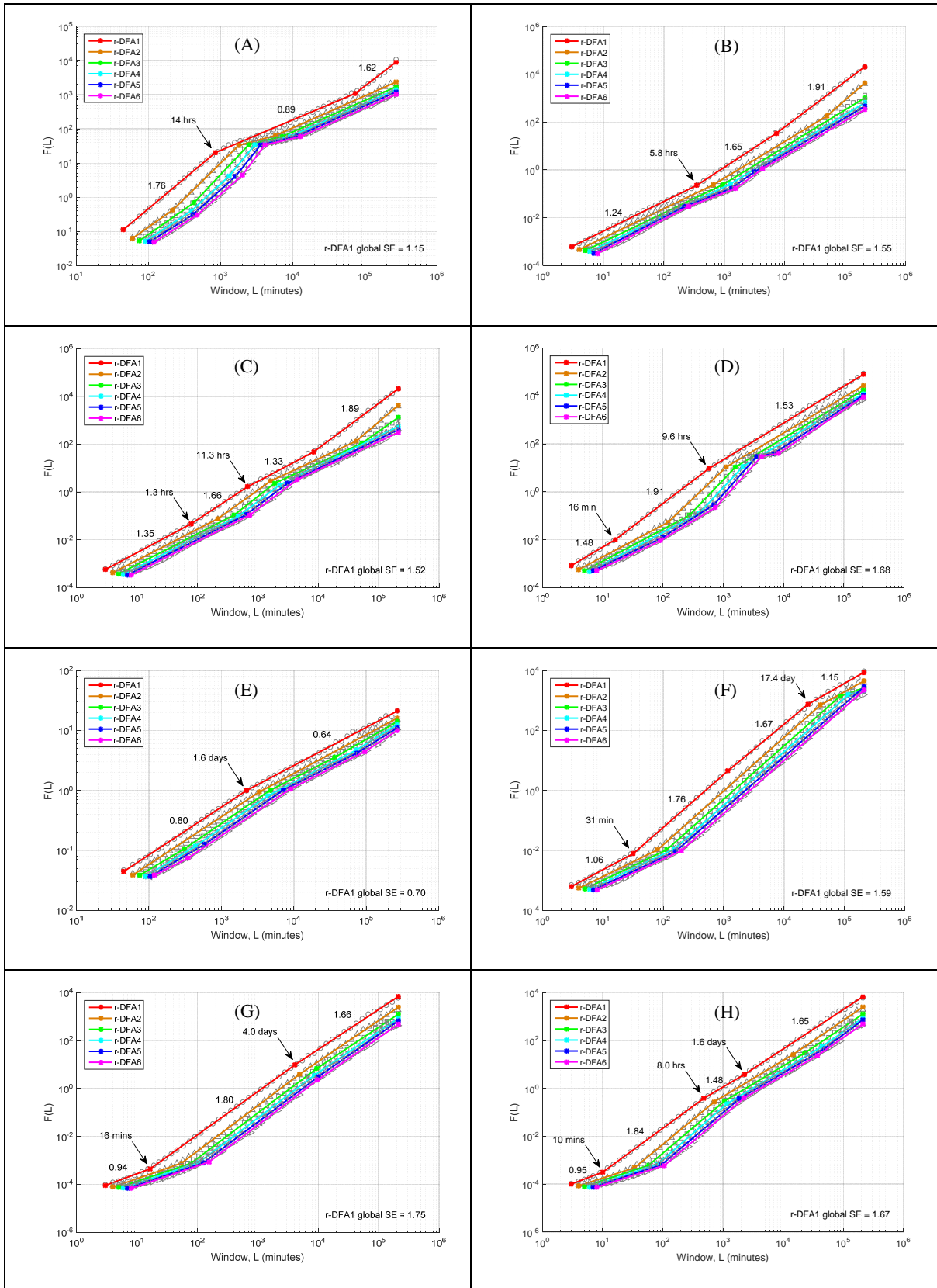
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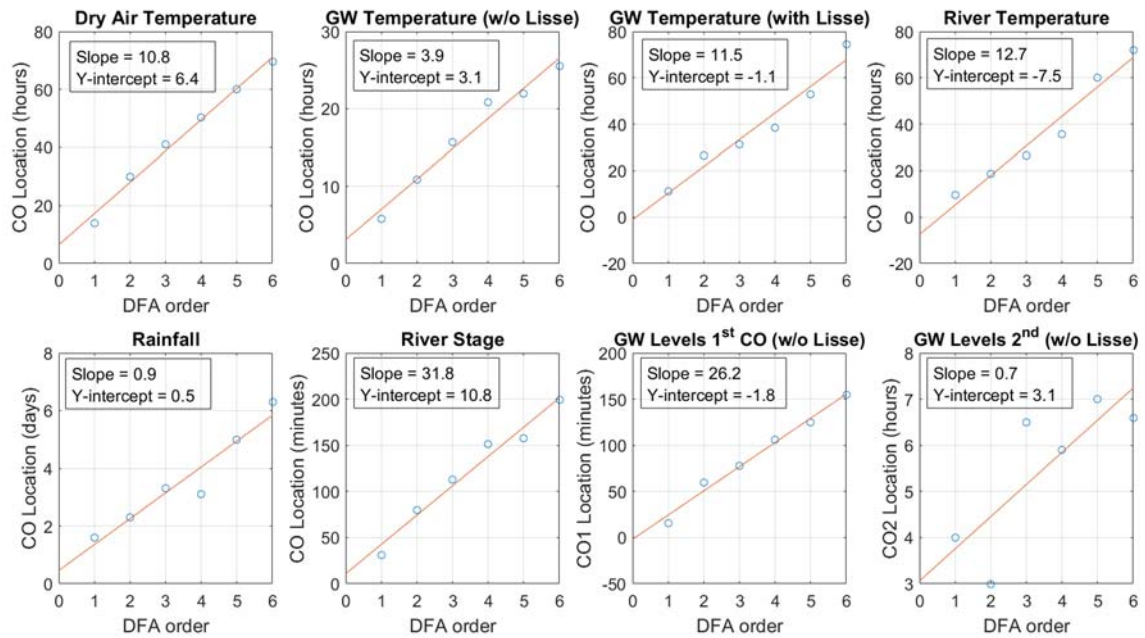


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619 Figure 13 r-DFA results of (A) dry air temperature, (B) 1-minute groundwater temperature corrected for
 620 Lisse effect, (C) 1-minute observed groundwater temperature, (D) 1-minute river temperature, (E) 15-minute

621 rainfall intensity, (F) 1-minute river stage, (G) 1-minute groundwater level corrected for Lisse effect, and (H) 1-
 622 minute observed groundwater level

623



624

625 Figure 14 Summary of COs that persist through all orders of DFA for all datasets studied

626

627 Table 1 All datasets analysed for fractal behaviour

Dataset	Resolution (minutes)	Data length
Dry air temperature	15	01/2012 to 12/2015
River Thames temperature Wallingford	1	01/2012 to 12/2015
Groundwater temperature at Wallingford (with and without the Lisse effect)	1	01/2012 to 12/2015
Rainfall at Wallingford	15	01/2012 to 12/2015
River stage at Wallingford	1	01/2012 to 12/2015
Groundwater levels at Wallingford (with and without the Lisse effect)	1	01/2012 to 12/2015

628

Table 2 Details of installations

Installation	Latitude (°)	Longitude (°)	Elevation (mAOD)	Total depth (m)	Screen (mBGL)
WL84	51.6036	-1.1107	47.883	5.01	2.17 - 4.71
WL85	51.6036	-1.1106	47.778	4.79	1.95 - 4.49
Thames stilling well	51.6047	-1.1164	43.747	N/A	N/A
AWS				N/A	N/A

Table 3 Data infilling and data flags

Data flags	Infilling technique	Groundwater		Thames	
		Level	Temp	Level	Temp
1	None	2050767	2050729	2054175	2054217
2	Linear interpolation (<10 min)	1173	1189	901	902
3	Linear regression	8281	256	93	50
4	Duplication of preceding record	1991	0	0	0
5	Linear interpolation (>10 min)	0	10038	7043	7043

Table 4 Summary of r-DFA results for all the time series analysed

Dataset	Resolution	r-DFA1			
		Global SE	CO 1	CO 2	CO 3
Air Temperature	15 min	1.15	-	14 hr	-
GW Temperature (observed)	1 min	1.52	78 min	11 hr	-
River Temperature	1 min	1.68	16 min	9.6 hr	-
Rainfall Intensity	15 min	0.80	-	-	1.6 day
GWL (observed)	1 min	1.67	10 min	8 hr	1.6 day
River Stage	1 min	1.59	31 min	-	17.4 day
GW Temperature (no Lisse)	1 min	1.55	-	5.8 hr	-
GWL (no Lisse)	1 min	1.75	16 min	4.0 hr	-

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Appendix A – Procedure for the removal of the Lisse effect

In the absence of soil air pressure data and other identifiers that would indicate a Lisse event from one that is otherwise, the following systematic approach was implemented for the removal of the Lisse effect:

- Gradients in the time series that exceed a pre-defined positive and negative threshold are identified. In this way the start and end of a Lisse event are identified. The thresholds are selected based on the probability density function of the slopes and on trial and error.
- Data points identified as being within a Lisse event are clustered using K-means clustering in order to segregate individual Lisse events.
- The clustering was assessed visually, and if necessary, amended.
- A linear slope joining the start and end of each Lisse event was computed to replace the Lisse event.

Figure A. 1 illustrates some Lisse events observed in the GWL data from Wallingford and the computed linear slope that will replace them.

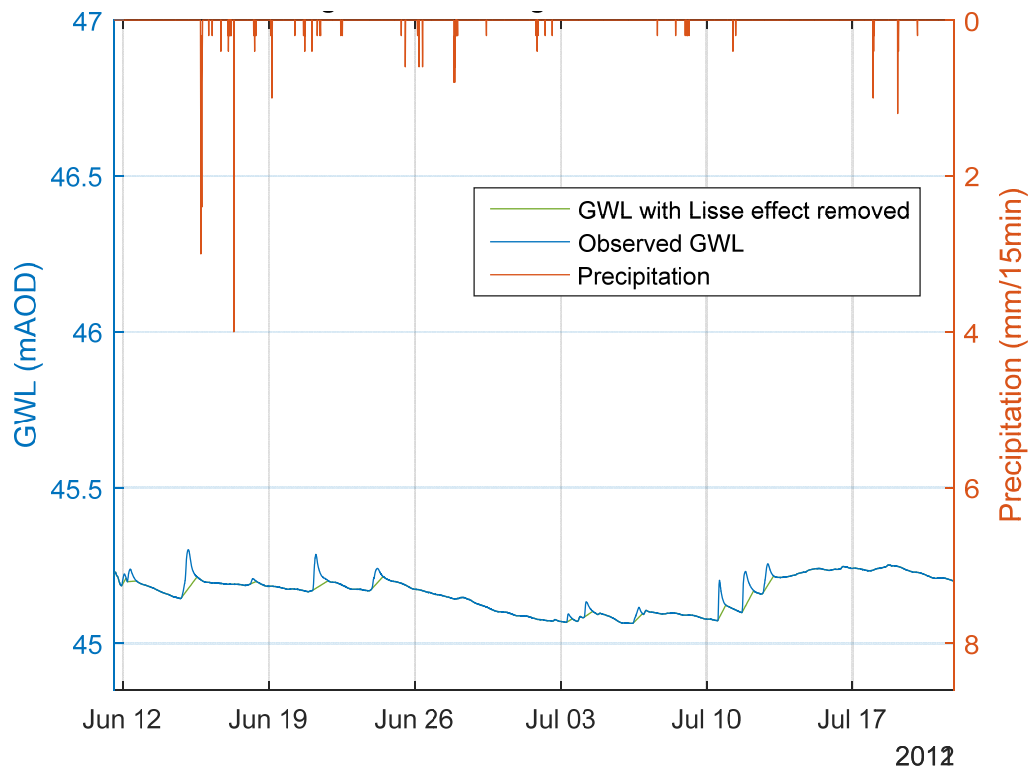


Figure A. 1 Illustration of the removal of some Lisse events from the Wallingford site