

Areal models for spatially coherent trend detection: the case of British peak river flows

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Key Points:

- We propose a novel approach to regional detection of trends in measured series based on areal models
- We detect a clear signal that peak flows magnitudes are increasing over time in Great Britain
- These changes are still found when different periods of record are analysed, with an accelerated upward trend from 1980 onward

Abstract With increasing concerns on the impacts of climate change, there is wide interest in understanding whether hydrometric and environmental series display any sort of trend. Many studies however, focus on the analysis of highly variable individual series at each measuring location. We propose a novel and straightforward approach to trend detection, modelling the test statistic for trend at each location via an areal model in which the information across measuring locations is pooled together. We exemplify the method with a detailed study of change in high flows in Great Britain. Using areal models, we detect a statistically relevant signal for a positive trend across Great Britain in the recent decades. This evidence is also found when different temporal subsets of the records are analysed. Further, the model identifies areas where the increase has been higher or lower than average, thus providing a way to prioritise intervention.

Plain language summary With growing concerns over the potential impacts of climate change, many studies are investigating whether river extremes, such as floods, are changing. Studies based on climate change projections indicate that changes might be expected in several parts of the world, including Great Britain where floods are predicted to increase. However, studies investigating measured river flow records have mostly found inconclusive evidence of change. This does not mean that change is not happening, but finding the evidence of this change is difficult because flow records are short and very variable. In this study we suggest that river flow measuring stations on the same river will experience similar changes since they are affected by the same climate. We therefore propose to use advanced statistical models which combine information from nearby stations and apply these model to high flows measurements in Great Britain. The analysis of data from closely located measuring stations demonstrates that flows have generally become bigger in Great Britain recently. The methods proposed in the manuscript could be easily applied to other type of data routinely measured and which might have been changing over time as a result of climate change or other drivers.

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1 Introduction

River flooding is a major natural hazard which threatens the well-being of communities and can have extremely high costs: the global annual average loss from river flooding is estimated to be USD 104 billion (United Nations Office for Disaster Risk Reduction (UNISDR), 2015) and in the United Kingdom (UK) alone the expected annual flood damages is GBP 560 million (Sayers et al., 2015). There is a widespread interest in understanding how climate change impacts fluvial flood risk (IPCC, 2012) so that appropriate management strategies can be put in place. This interest has resulted in a number of studies investigating projected and observed changes in peak flow magnitude (and/or frequency) at the global (Hirabayashi et al., 2013; Do et al., 2017), continental (Alfieri et al., 2015; Mediero et al., 2015) and national or regional scale (Giuntoli et al., 2015; Slater & Villarini, 2016; Kay et al., 2014a; Prosdocimi et al., 2014). The overall picture gives mixed results, with high flows projected to increase and decrease in different areas of the world under representative concentration pathway RCP8.5 (Dankers et al., 2014), while for the UK national scale investigations based on the UKCP09 projections (Murphy et al., 2009) under a range of emission scenarios (Kay et al., 2014a, 2014b) indicate an overall increase in high flows in the last decades of the 21st century. In contrast, studies based on gauged historical data give a more faceted picture, in the UK as well as in other parts of the world (Hannaford, 2015; Hall et al., 2014; Archfield et al., 2016), with no clear detectable changes in the behaviour of high flows.

Failure to detect a clear time trend signal in gauged peak flows (or other environmental variables) does not necessarily mean that an overall trend does not exist: the absence of evidence for change does not give evidence for the absence of change. Most statistical approaches used for trend detection would need very long records to perform optimally (Svensson et al., 2006), and such long records are sparse in Britain (see Figure S1 and S2) and generally across the world. In particular, tests applied to short time series have low statistical power, i.e. they are not able to detect signals of change even when these are present in the data (Vogel et al., 2013; Prosdocimi et al., 2014). To overcome this lack of power, we develop an areal model which pools information across stations in the same geographical region to enhance the shared trend signal. Areal models can be viewed as multilevel or hierarchical models (see Gelman et al. (2013); Verbeke and Molenberghs (2009)), which are routinely used in life sciences and social sciences to obtain a clearer estimation of the phenomena under study by pooling together the information across several observations (see for example Gelman et al. (2012)). By pooling together the information of nearby stations the signal for the evidence of change, and in particular of an increase in flow magnitudes, is enhanced and becomes very clear.

2 Data

We use the annual maxima of the instantaneous (15-minute) gauged peak flow recorded at 640 stations in Great Britain (GB) made available by the National River Flow Archive (2018). This is a subset of the national *Peak Flow Dataset* which is maintained by the National RiverFlow Archive (NRFA) and is the successor of HiFlows-UK, the reference dataset used in the UK to carry out flood estimation studies (Lamb et al., 2009; Environment Agency, 2012). Annual maxima are selected as the highest flow value registered in any given water year, which in the UK runs from October 1st to September 31st. In this study we used flow values for all the years of station records deemed to have reliable rating curves up to, at least, bank full flow. This ensures that the data series which the measuring authorities deem to be of the highest quality and reliable throughout the recording period are included in the study. To ensure that the results can be indicative of the impacts of (anthropogenic) climate change, only records which end in a year subsequent to the water year 2000 and which refer to catchments with low levels of urban land-cover are included. Finally, only stations with more than 20 years of data are retained in the study. This results in the inclusion of a total of 640 stations with a median

97 length of 47 years: see Text S1 for additional information on the spatio-temporal cov-
 98 erage of the records used in this study.

99 For practical reasons, river flow measurement and hydrometric data collection in
 100 the UK are organised on a catchment or basin basis, rather than according to the ad-
 101 ministrative boundaries. Therefore the country has been divided into 107 hydrometric
 102 areas (HA, National River Flow Archive (2014)) which consist in integral river catch-
 103 ments having one or more outlets to the sea or tidal estuary. Of the 107 British HAs,
 104 97 are located in mainland Britain and stations with high quality annual maxima records
 105 are available in 90 of those. Each station is located in a specific HA, and these are de-
 106 fined based on river systems which typically experience similar climate and weather (see
 107 Text S3 for an exploration of the climatology of the HAs), with some of the catchments
 108 within each HA possibly nested within each other (and therefore not independent from
 109 each other). HAs are based on geophysical properties of river basins and were designed
 110 to facilitate an integrated approach to the collection of hydro-meteorological data: their
 111 definition is independent of the study of trends in river flow, and as such is an objective
 112 way to separate stations into groups which can be expected to behave similarly. We will
 113 therefore use the hydrometric areas in the spatial model outlined in the next section. Fig-
 114 ure S2 shows how the different hydrometric areas span across the countries in Great Britain.

115 3 Methods

116 For each station in the study a simple regression is performed on the log-transformed
 117 river flow with time as a covariate, as in Vogel et al. (2011) and Prosdocimi et al. (2014).
 118 For each station i , the value of the test statistic for the significance of time T_i is derived.
 119 Time here is used as a proxy for anthropogenic climate change, and the test statistic T_i
 120 is a standardised summary of the evidence in favour of a time trend, so of a change, at
 121 each station i (see Text S2 for more discussion on the derivation of the test statistic).
 122 Stations are located in one HAs only, with each HA typically experiencing similar cli-
 123 mate and weather (see Text S3). It is therefore conceivable that similar changes occur
 124 at different locations within each HA, so that the test statistic value of stations within
 125 each HA should be similar in sign and magnitude and can be pooled together to give a
 126 clearer indication for the potential of change in the specific HA and across Great Britain.

127 An areal model for the test statistic is therefore constructed so that the value of
 128 the test statistic at each station is modelled as the random variation around the sum of
 129 the average value μ and an areal component h_j which can take different values for each
 130 HA j . This is written as (see, among others, Lawson (2013))

$$T_i = \mu + h_{j(i)} + \eta_i \quad (1)$$

131 where μ is the mean signal for trend across HAs, $h_{j(i)}$ is a parameter taking specific value
 132 for the hydrometric area j to which the station i belongs and $\eta_i \sim N(0, \sigma_T^2)$ is the station-
 133 specific random error. This model implies that the test statistic at each station i in a
 134 region j is the realisation of a random variation around the regional value $\mu+h_j$. It is
 135 assumed that the effects h_j for each hydrometric area are independent and identically
 136 distributed (iid) with $h_j \sim N(0, \sigma_H^2)$. The h_j 's are unknown random quantities that
 137 reflect our belief that variability of the test statistic within region j is likely to be smaller
 138 than the overall variability of the test statistic. The parameters which need to be esti-
 139 mated from the data are μ , σ_H and σ_T : this is done in a Bayesian fashion using R-INLA
 140 (Rue et al., 2009) which allows for fast approximate estimation of complex models. This
 141 means that the posterior distributions of the model parameters given the observed data
 142 (i.e. the observed test statistic values) are estimated. Stations within each HA would then
 143 have the same estimated posterior distribution for the test statistic in the areal model,
 144 an indication of the strength of evidence for a trend in an HA averaged across all sta-
 145 tions within the area. From this posterior probability, the evidence for either a positive,
 146 negative or null trend can be derived.

147 The parameters are estimated by pooling the information from all stations in the
 148 network, thereby using the available information in an optimal way. The overall level μ
 149 gives an indication of the strength of evidence in favour of a trend across the parts of
 150 Great Britain included in this study. More specifically, the posterior estimate of μ is ap-
 151 proximately the average of all HA sample averages (where by ‘‘HA sample average’’ we
 152 mean the average of the observed test statistics within a given HA). In particular, the
 153 pooling in the area-level model means that the posterior estimate of μ is robust to dif-
 154 ferences in the number of stations per HA. For a given HA, the posterior estimate of the
 155 test statistic in this HA is approximately the weighted sum of its HA sample average and
 156 the estimated overall trend μ . The weight on the HA sample average increases as the
 157 number of stations in the HA increases, meaning the posterior evidence of trend in an
 158 HA with many stations is less influenced by pooling than in HAs with sparser data. De-
 159 tails of the estimation theory for partial pooling models such as the areal model presented
 160 in equation (1) can be found in Gelman and Hill (2012) - Chapter 12.

161 A number of approaches to pool information in space have been proposed for the
 162 detection of trends in environmental variables (see for example Renard et al. (2008); Fis-
 163 cher and Knutti (2014)), and some of these make use of Bayesian hierarchical models (e.g.
 164 in Renard et al. (2006); Brady et al. (2019)). The areal model proposed has the advan-
 165 tage of using as the response variable the test statistic, a simple concept which is typi-
 166 cally easy to compute, is normalised and has a well defined theoretical distribution un-
 167 der the null hypothesis of no-change. After choosing a spatial aggregation unit (in this
 168 manuscript, the externally pre-determined HA), it is straightforward to derive informa-
 169 tion about the posterior distribution of the average test statistic at each aggregation unit,
 170 and to identify the areas with high probabilities for the test statistic to be different from
 171 0, i.e. an indication of change in the original variable of interest. In this study we pro-
 172 pose to use HAs as the spatial aggregation unit, as these have been defined independently
 173 for hydrometry purposes and are commonly used in practice to identify river basins and
 174 coherent areas for water management purposes. Other aggregations might be used, pos-
 175 sibly not based on geographical proximity, but based on, for example, flood generating
 176 mechanism or other similarity measure. Nevertheless results for different aggregations
 177 would be more difficult to visualise on a map and the interpretation of the results would
 178 be less direct since it would not be related to a specific area and river basin.

179 4 Results

180 Figure 1 (left panel) exemplifies the ambiguous results typically found when ap-
 181 plying a statistical test on a site by site basis to all stations in a river gauging network.
 182 The figure shows the values of a test statistic for the time trend derived according to the
 183 method outlined in Section 3 and further discussed in Text S2.

184 For a vast majority of stations (71%) the test statistic is not significant at the 10%
 185 significance level indicating that the null-hypothesis of no change (i.e. no trend) in time
 186 cannot be rejected. As discussed in Prosdocimi et al. (2014) this might be connected to
 187 the low statistical power of the test applied to short time series. For 4% of stations a sig-
 188 nificant negative trend is found, while positive significant trends are found in 25% of sta-
 189 tions. There is therefore an indication that positive trends are more frequent than neg-
 190 ative trends, and there appears to be some spatial clustering of positive trends in North-
 191 western England and parts of Scotland. The tendency of the test statistic of all stations
 192 to be positive rather than negative is also evident in the general distribution of the test
 193 statistics, which is shown in Figure S3.

194 The central and right panel of Figure 1 summarise key results of the areal model
 195 fit, highlighting a clear positive trend signal when regional information is pooled together
 196 (estimates for the variance components are presented in Table S1 and Text S5). The map
 197 in the middle panel shows the mean value of the estimated posterior distribution of the
 198 test statistic for each HA: these tend to be positive, with only few areas exhibiting slightly

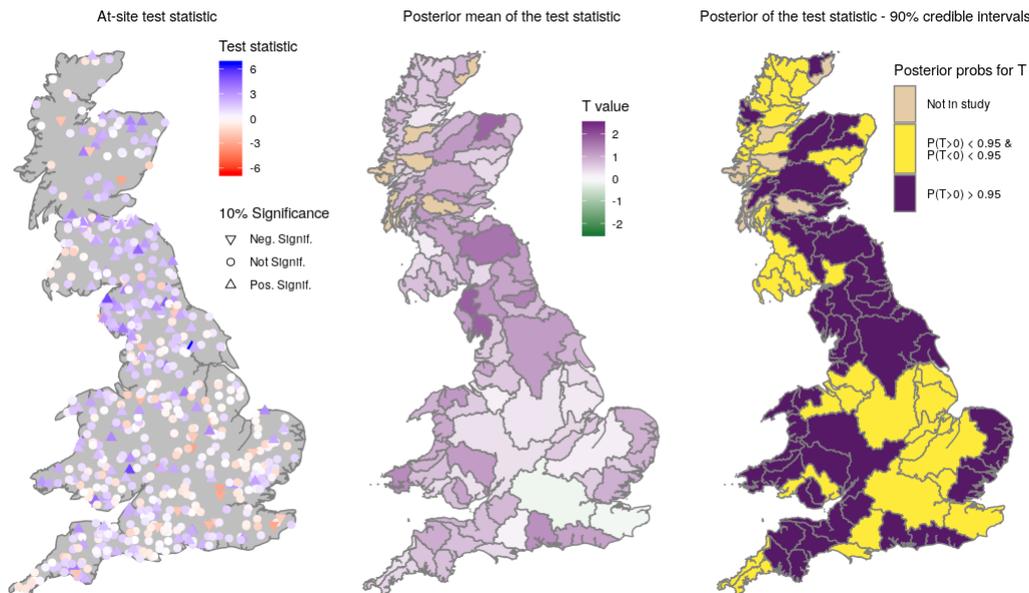


Figure 1. Left panel: at-site test statistic and significance at 10% level for all stations. Central panel: estimated posterior mean derived from the proposed areal model for each area specific test statistic value. Right panel: summarised information for the 90% credible interval for each area specific test statistic value.

199 negative values. The 90% credible interval for the overall trend μ is (0.64, 0.91). Thus,
 200 there is a tendency for increasing trends across the river flow measuring network in the
 201 country. For 54 out of 90 areas the entire 90% credible interval for the mean test statis-
 202 tic is positive, i.e. more than 95% of the posterior distribution of the area specific test
 203 statistic value is larger than 0 (purple HAs in the right panel of Figure 1). For no HA
 204 in the country does the 90% credible interval of the marginal posterior distribution of
 205 the area specific test statistic contain negative numbers; this shows that across the river
 206 flow measuring network in GB there is an either null or positive trend. The strongest
 207 signal in favour of trend is found in northern England, parts of Scotland and Wales and
 208 the weakest signal is found in Southern and Central England. This indicates that these
 209 areas might need to be given higher, respectively lower, priority for a new flood risk as-
 210 sessment. Some spatially structured variation in the estimated strength of the trend in
 211 the different HAs can be noted, even though the model does not specifically enforce this.
 212 This might indicate that large scale climate variability, which operates on a large spa-
 213 tial scale, is a large driver of the changes in high flows. These findings are not dissim-
 214 ilar when robust regression approaches are used in the derivation of the test statistic (see
 215 Text S6).

216 The wide range of posterior mean values in the different HAs is possibly the result
 217 of very different patterns of change for high flows in different areas of the UK. This di-
 218 versity in trend directions has already been highlighted (Hannaford, 2015), but the areal
 219 model allows to separate out an island wide effect and the areas which have experienced
 220 coherent changes in high flows. Nevertheless, a more HA specific analysis would be needed
 221 to identify the possible causes behind the evidence for change (or lack thereof) in any
 222 area: local factors and the response of single catchments to external forcings can have
 223 strong impact in the final estimated value of the test statistic for each station in the HA.
 224 These local factors are not directly included in the areal model but would need to be taken
 225 into account in any assessment of the evidence for a trend within a HA.

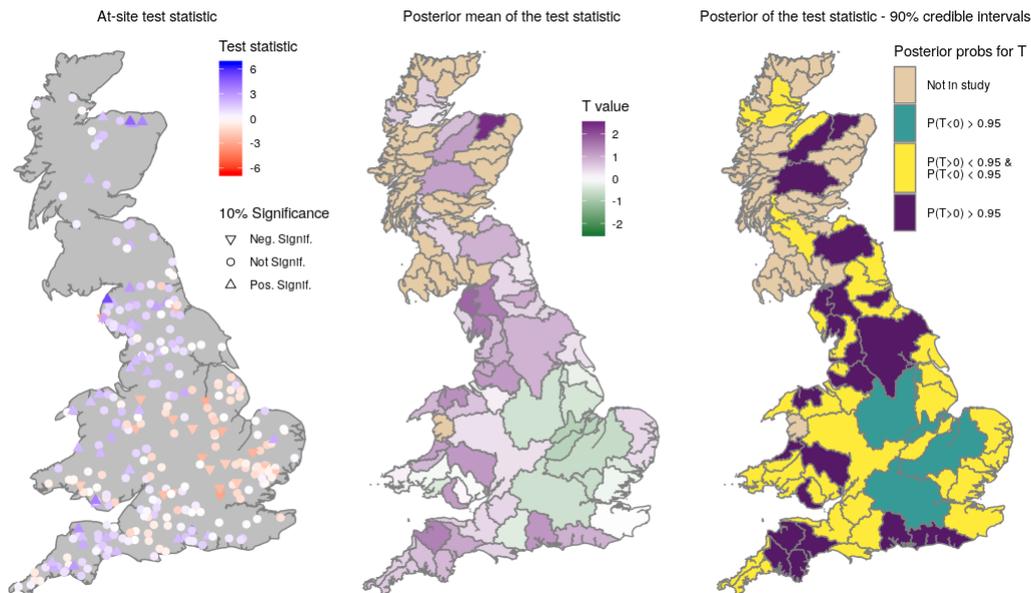


Figure 2. Results for a long common time period analysis (1976-2016). Left panel: at-site test statistic values and significance at 10% significance level for all stations. Central panel: estimated posterior mean derived from the proposed areal model for each area specific test statistic value. Right panel: summarised information for the 90% credible interval for each area specific test statistic value.

226 The period of record covered by the data can have an influence on the estimated
 227 magnitude and sign of the tests which aim to identify monotonic trends (Svensson et al.,
 228 2006; Hannaford et al., 2013), and tests applied to data covering different periods might
 229 give contrasting results. As seen in Figure S1 and S2, the flow series available in GB cover
 230 different periods of time, with a few very long records and most stations having valid records
 231 starting in the 1970s. The overall trend μ and the HA specific signals found in the anal-
 232 ysis might therefore be representative of different types of changes, and the strong evi-
 233 dence for trend cannot be directly related to a change in peak flow behaviour over a spe-
 234 cific period of time. Therefore we carry out a second analysis which focuses on a sub-
 235 set of stations over a fixed period of time. The analysis uses the 298 stations with com-
 236 plete records between 1976 and 2016 (included), i.e. with a total of 41 consecutive years
 237 of data. The location of the gauging stations included in the study and the value for the
 238 time trend test statistic at each station are shown in Figure 2, together with results of
 239 the areal model fitted to the data subset (estimates for the variance components are pre-
 240 sented in Table S2 and Text S5). The 90% credible interval for the overall trend signal
 241 across the river flow measuring network in GB μ is now found to be (0.31, 0.72): the evi-
 242 dence for trend is not as large as when all records are used but it is still strong and pos-
 243 itive. The posterior mean of the test statistic is found to be negative in 15 out of 65 areas,
 244 with the entire 90% credible interval below 0 in 4 of them (the green HAs in the right
 245 panel in Figure 2). Changing the time window of the investigation gives a less striking
 246 result, but still indicates that overall peak flow magnitude is increasing throughout the
 247 country.

248 To further assess the evidence in favour of a changing behaviour of peak flows, the
 249 subset of stations with exactly 41 years of data was further analysed taking 10 subsets
 250 of 31 consecutive years of data with changing initial year (from 1976 to 1985). The es-

251 timated posterior distribution for the overall trend parameter μ in the different sub-periods
252 is shown in Figure 3: across all sub-periods the overall trend is generally positive, and
253 for no sub-period does the 90% credible interval contain 0. The lowest posterior mean
254 value (0.23) is found when analysing the 1979-2010 sub-period and the highest value (0.88)
255 is found when analysing the 1984-2015 sub-period. The water year 2010 was characterised
256 by a drought condition (Kendon et al., 2013), while several record breaking flood events
257 were recorded in 2015 (Barker et al., 2016). Notice also that 1984 was characterised by
258 strong drought conditions (Marsh & Lees, 1985): this might further enhance the strength
259 of the signal for the 1984-2015 period. The difference in the overall effect in the two pe-
260 riods is likely to be a reflection of the general behaviour of peak flows in the final and
261 start year of the analysis. In general, the analysis ending in water year 2007 to 2010 in-
262 dicate an increase in high flows with a smooth decline in time for the overall trend de-
263 scribing the increase. In contrast, the analysis based on records ending in the most re-
264 cent six years have stronger signals in favour of a change with more variability across each
265 sub-analysis. This indicates that the overall signal μ increases in each sub-analysis, cul-
266 minating in a very large estimated value μ found when the record breaking water year
267 2015 is included in the analysis. This very strong indication for an increase in flood risk
268 is then followed by a much milder signal when the records including the more modest
269 water year 2016 are also included in the analysis. The estimated area specific posterior
270 mean found for each data subset are shown in Figure S5, with the summary of the cred-
271 ible interval in Figure S6. Regardless of the observation period used in the analysis, there
272 is an indication that peak flow magnitudes are increasing across GB, with a stronger and
273 more persistent signal in the northern part of England and parts of Scotland, while there
274 appear to be less of a concern for changes in high flows in the south-east of England. This
275 finding still holds true when the test statistics included in the areal model are derived
276 from a robust regression model (see Text S6). Even when ensuring that the large records
277 in some series in the latter years are less influential in the estimation of the regression
278 model at each station, a strong evidence for an increase in peak flow is found.

279 The length of the period for which it is possible to run sub-analyses in which a con-
280 siderable number of stations has a complete record is unfortunately fairly limited, and
281 does not allow for more in depth analyses of the possible large scale climatic drivers linked
282 with unusually high or low peak flows at a country-wide scale. Climate modes typically
283 evolve slowly in time with persistent periods of positive or negative anomalies, which can
284 impact the behaviours of high flows. For example, modes of the Atlantic Multidecadal
285 Oscillation (AMO) and of the North Atlantic Oscillation (NAO) have been linked to pe-
286 riod of elevated high flows in Europe and North America (Hodgkins et al., 2017) and in
287 GB (Hannaford, 2015); thus linking the occurrence of flood rich periods to multidecadal
288 variability rather than to long-term time trends. Given that in the short time scales for
289 which most flow records are available climate indices have been slowly varying, the de-
290 tected changes might be a consequence of the dominance of a climatic state rather than
291 a time-related trend.

292 5 Discussion and conclusions

293 The natural high variability typical of short environmental records such as peak
294 flow data and the lack of long records has previously hindered the ability of at-site tests
295 to identify clear signals of change in high river flow across large regions (Prosdocimi et
296 al., 2014; Mallakpour & Villarini, 2015). In this study, we use areal models to pool to-
297 gether the information that directly measure the strength of the evidence a change in
298 peak flows over time across all stations. Using this approach, we find strong evidence for
299 a positive trend in the magnitude of gauged annual maxima of peak river flow in Great
300 Britain. This holds true when different subsets of the available records are analysed and
301 when using robust regression approaches in the derivation of the test statistic. The sig-
302 nal is clearly detected when all test statistic values across the island are modelled simul-
303 taneously in an areal model. These results are in line with those in Brady et al. (2019),

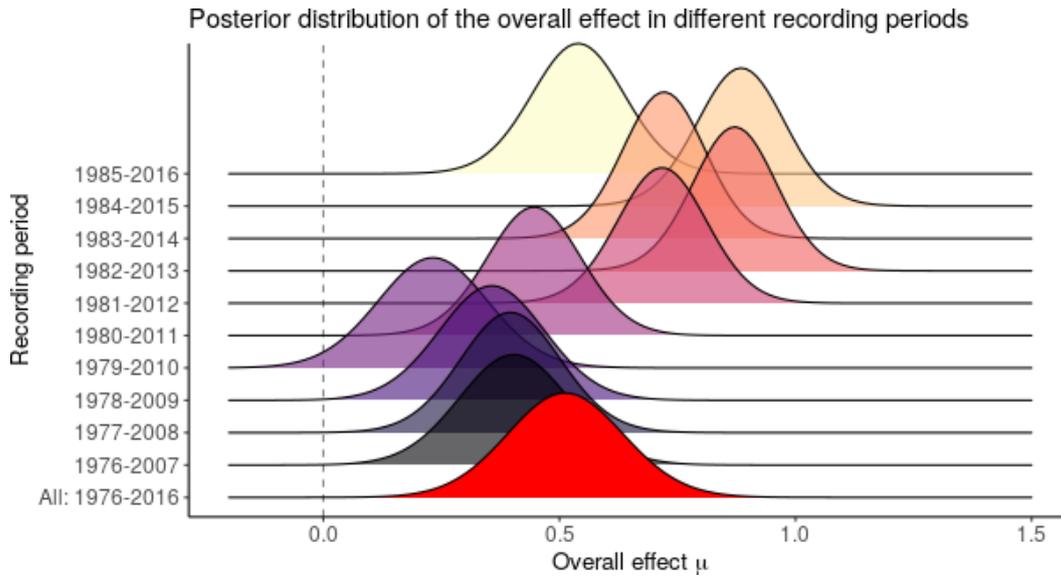


Figure 3. Estimated posterior distributions of μ when using different 31-year long subsets and the 41-year long subset in the period 1976-2016.

304 in which a similar strength in change in time in near natural catchments was identified
 305 using more complex and computationally demanding spatial models. Exploiting the spa-
 306 tial structure of the flow data enhances the trend signal and allows for a clearer infer-
 307 ence, thus bridging the previously reported discrepancy between the projected increases
 308 in flood risk in GB and the lack of clear signal in the observational peak flow records.
 309 Further, the model identifies areas for which the area-specific evidence for a (positive)
 310 trend is strong, allowing for a spatial characterisation of the potential changes in floods.
 311 These areas would be the natural candidates for more in-depth analysis of changes in
 312 flood frequencies.

313 In this study we do not attempt to explain the driving causes which lead to the ob-
 314 served change, but rather focus on presenting strong evidence that a change has indeed
 315 occurred. The fact that the high flows in the most recent years appear to have on av-
 316 erage higher values than those in the past does pose a challenge in terms of whether the
 317 full record available at each station should be used when estimating flood frequencies and
 318 whether some adjustments should be put in place to account for the fact that estimates
 319 obtained using the whole record might underestimate the current flood frequencies (see
 320 for example (Luke et al., 2017) for a suggestion of such a correction). The approach pre-
 321 sented in this study could easily be applied to other parts of the world and other types
 322 of environmental data: pooling the information on the strength of trend at different sta-
 323 tions will likely enhance the ability of detecting clearer signals of change across large mea-
 324 suring networks.

325

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Supporting Information for “Areal models for spatially coherent trend detection: the case of British peak river flows”

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Contents of this file

1. Text S1 to S6
2. Figures S1 to S8
3. Tables S1 to S2

Additional Supporting Information (Files uploaded separately)

1. `dataPreparation.R`: R file to create the datasets underpinning the analysis

2. `dataAnalysisAndFigures.R`: R file to carry out the analysis and create the Figures and Tables presented in the paper and in the Supplementary Information

The two are files can also be found at <http://doi.org/10.5281/zenodo.3497404>

Introduction

The supplementary information is sub-divided in 6 main topics, each within a Text block which introduces the relevant Figures and Tables. Text S1 presents some additional information on the spatio-temporal coverage of the river flow data used in the study. Text S2 gives some additional background on the derivation of the test statistics used in the analysis. Text S3 gives some additional information on the climatology of Great Britain and on the similarity in climate within hydrometric areas. Text S4 shows the estimated posterior mean and credible intervals for the areal models derived in each sub-analysis on the long common period. Text S5 shows summary statistics for the estimated posterior of parameters of the areal models, including the variance components. Text S6 presents the results obtained when using the test statistics derived using robust regression.

Text S1.

Available flow records

Figure S1 and S2 show the temporal evolution of the record availability across Great Britain. The drop in data availability after the early 2000s visible in Figure S1 is due to a delay in the processing of the gauged data by the Scottish measuring authorities, as evident in Supplementary Figure S2. Figure S2 also shows what portions of Great Britain and of the hydrometric areas are located in England, Wales or Scotland.

Text S2.*Test statistic for a linear trend*

We used a simple linear regression model applied to the logarithm of peak flow with time as an explanatory variable to assess whether or not there are trends in the magnitude of peak flow at each station:

$$\log(Q_{wy}) = \alpha + \beta wy + \varepsilon_{wy} \quad (1)$$

where $\varepsilon_{wy} \sim N(0, \sigma^2)$ for every wy , and α , β and σ are parameters which need to be estimated. In the notation above wy represents the water year in which the high flow value Q_{wy} was measured, and it varies between (wy_1, \dots, wy_n) , with wy_1 being the first year in the record and wy_n being the last year in the record. The Q_{wy} variable represents the annual maximum peak flow value (measured in m^3/s). This model was introduced by Vogel, Yaindl, and Walter (2011) and applied to the British data in Prosdocimi, Kjeldsen, and Svensson (2014), where it was found to fit well the British data.

At each station, the trend parameter β is estimated as

$$\hat{\beta} = \rho(Q, wy) \frac{sd(Q)}{sd(wy)}$$

where $\rho(Q, wy)$ is the sample correlation coefficient between peak river flow series and the time variable, while $sd(Q)$ and $sd(wy)$ are, respectively, the sample standard deviation of the peak river flow series and the time variable. The standard deviation of the trend estimate can be derived using standard results for linear regression models as:

$$sd(\hat{\beta}) = \sqrt{\frac{\hat{\sigma}^2}{\sum_{i=1}^n (wy_i - \overline{wy})^2}}$$

where $\hat{\sigma}$ indicates the estimate for regression error, which can be derived as $\hat{\sigma} = sd(Q) * \sqrt{(1 - \rho(Q, wy)^2)}$, and \overline{wy} indicates the average value of the time variable. A test statistic for trend, i.e. for the system of hypothesis

$$H_0 : \beta = 0 \quad VS \quad H_1 : \beta \neq 0$$

can therefore be constructed as

$$T = \frac{\hat{\beta}}{sd(\hat{\beta})}.$$

According to the statistical theory, under the null hypothesis the test statistic follows a T-distribution with $(n - 2)$ degrees of freedom, which resembles closely the standard normal distribution for relatively large values of n . By calculating the necessary quantities at each station separately a set of test statistic values (T_1, \dots, T_{640}) is derived. Each test statistic is a summary of the strength of the time trend at each station. The set of all test statistics is then modelled simultaneously by means of the areal model presented in the main text. A second set of test statistics $(T_1^R, \dots, T_{640}^R)$ is also derived for the same model in equation (1) and the same system of hypothesis for trend using a robust approach to linear regression estimation as presented in Yohai (1987). Under the null hypothesis of a null slope these test statistics are also asymptotically normally distributed. Using a robust approach ensures that the estimate of the slope in the linear model is not unduly affected by large flow events in the series. Although the main analysis focuses on the test statistics derived from standard liner models, the set of robust test statistics is used to ensure that the reported findings are not unduly influenced by some of the larger events recorded in the latter years in the records.

According to the statistical theory underlying the construction of the test, if the null hypothesis of no trend was true across all stations and the tests at each station were independent, we would expect the values of the test statistic across all stations to behave approximately like a standard normal distribution. Examining the overall distribution of test statistic values for the complete dataset in Figure S3, a misalignment to the theory is evident: the overall mean and standard deviation are found to be 0.733 and 1.36 and the histogram shown in the left panel of Figure S3 is clearly different from what we would expect to see if the test values behaved according to the standard normal distribution. This is also true for the case in which the 298 records with the long common time period (1976-2016) are used to calculate the test statistics (right panel). Possibly, this misalignment is a consequence of the fact that hypothesis of no trend does not hold overall and that the tests performed at each station are not independent, since nearby stations might gauge the same river and are affected by the same climate and weather.

Text S3.

Climatology of Great Britain and Hydrometric Areas

In the areal model introduced in the main text it is assumed that the evidence for trend is similar within each hydrometric area (and not that the flow records within each area are homogeneous). One of the reasons which justifies assuming that stations within each hydrometric areas can be expected to be experiencing a similar trend, is that they are located in similar climate, would experience similar weather and would in some cases be gauging different sub-catchments of the same river. To investigate how similar stations

within hydrometric areas might be from a climatological point of view, a map of the long term temperature and rainfall climatology across Great Britain is displayed in Figure S4, together with two measures of seasonality of the annual maximum flow at each station. These two measures are, the median day of peak flow and the modal (i.e. most frequent) month of peak flow at each station. These latter measures were derived from the annual maxima records: the water year in the UK begins on October 1st and all measures are derived accordingly, so a median day of flow equal to 1 would indicate that the median day of peak flow at the station is October 1st. The long term climatologies, derived from measurements in the years between 1981 and 2010, are provided at a 1 km grid resolution by the Met Office (2018). The presence of mountainous ranges is clearly detectable in both the rainfall and temperature maps. These ranges divide the country in a cooler and wetter north-western part, characterised also by a more marked winter seasonality and a drier, warmer part in which later peak flows are more common. Although for the HAs which contain the higher mountain peaks there might be some differences in the climatologies, with heavier rainfalls and cooler temperatures on the mountain tops, these HAs tend to include stations which are directly connected hydrologically, i.e. that gauge sub-catchments of the same river. Conversely, the HAs in which stations might be effectively gauging different river courses tend to be located in the southern part of the country, where the climate is more homogeneous.

Text S4.

Time evolution of evidence for trend across the long common period of record

Figure S5 and S6 show the evolution of the estimated posterior mean for each area specific test statistic value when using different 31-year long subsets of the data and the 41-year long subset in the period 1976-2016 (the long common period of record).

Text S5.

Inference for variance components in the areal models

In Table S1 key summary statistics for the marginal posterior distribution of the overall trend value and the variance components of the areal model presented in equation (1) of the main text are shown. The fairly high estimated values of the σ_H^2 variance component highlight the need for the area-specific effects h_j to be included in the model since their inclusion explains a large part of the variability in the data. This is also true for the model based on the records with a long common time period (1976-2016), for which key summary statistics are shown in Table S2.

Text S6.

Inference when the test statistics are derived using robust regression approaches

Figure S7 is structured as Figure 1 in the main text although the test statistics displayed on the left hand side map and on which the areal model is fitted corresponds to the test statistics derived using robust regression approaches rather than standard linear regression. The general findings using the alternative robust regression approaches are fairly similar to those found when using results based on the standard linear models. Some

variations are visible in the test statistic values and the properties of the posterior distribution in each HA. In particular for less areas is the 90% credible interval found to only include positive values, and in one case, HA 39, the Thames, the 90% credible interval is found to only include negative values. The 90% credible interval for the overall trend effect μ is (0.47, 0.73) which is slightly wider than that reported in the main text, but still does clearly not include the null value. The indication of strong evidence in favour of an increasing trend in river flow is still present.

This is still true also when the analysis is carried out on the long period of record and its subsets. Figure S8 is structured in the same way as Figure 3 in the main text. Although there is less variability in the posterior distributions in the different sub-periods, it is still clear that the overall trend is generally positive with no 90% credible interval in any sub-period containing negative values.

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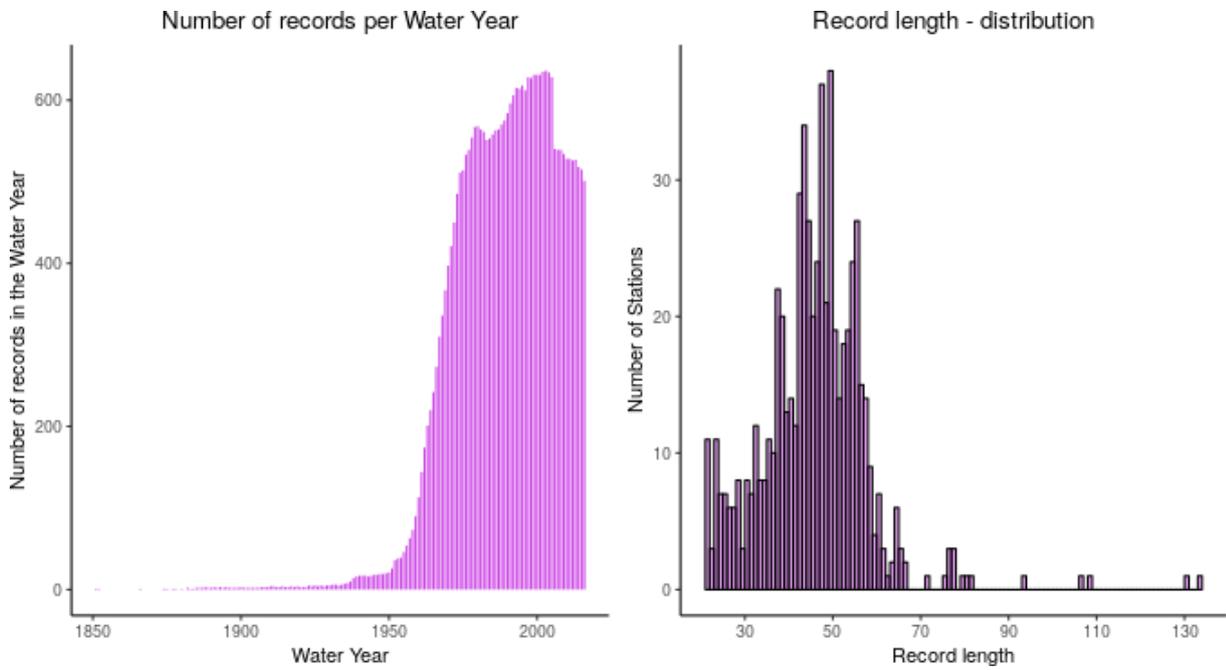


Figure S1. Left panel: number of records available per year. Right panel: histogram of the record length available at each station.

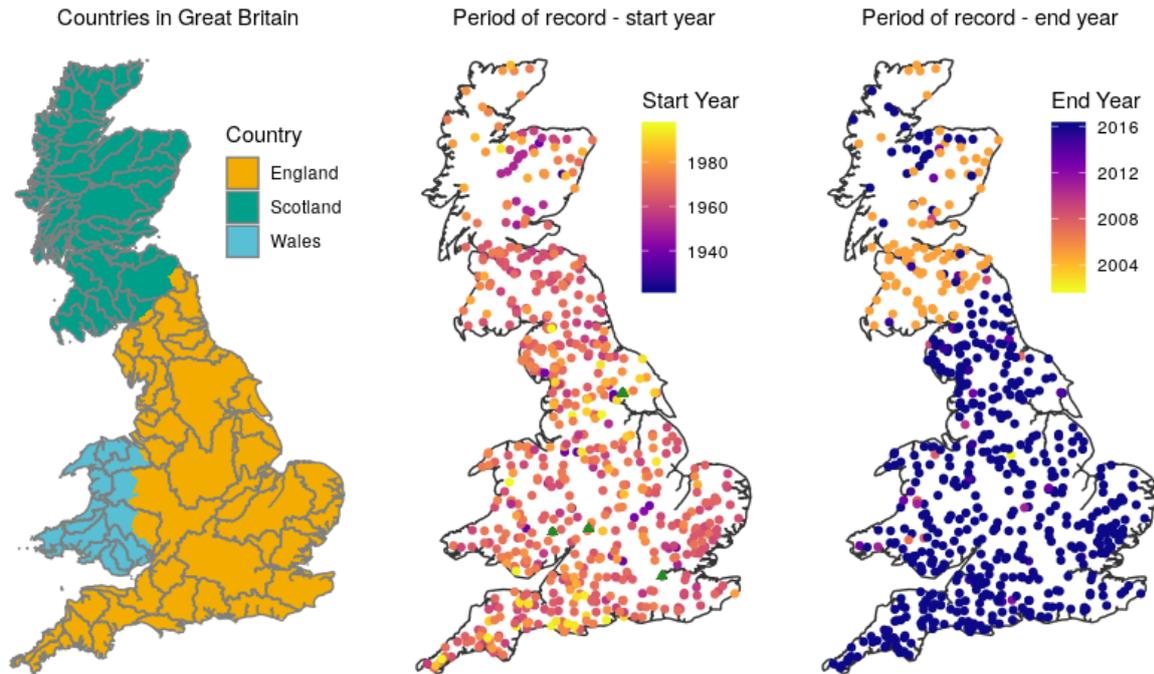


Figure S2. Left panel: division of Great Britain according to the country, including hydrometric areas (HA). Central panel: first year of valid flow measurements at each station (green triangles indicate stations which began recording before 1916). Right panel: last year of valid flow measurements at each station.

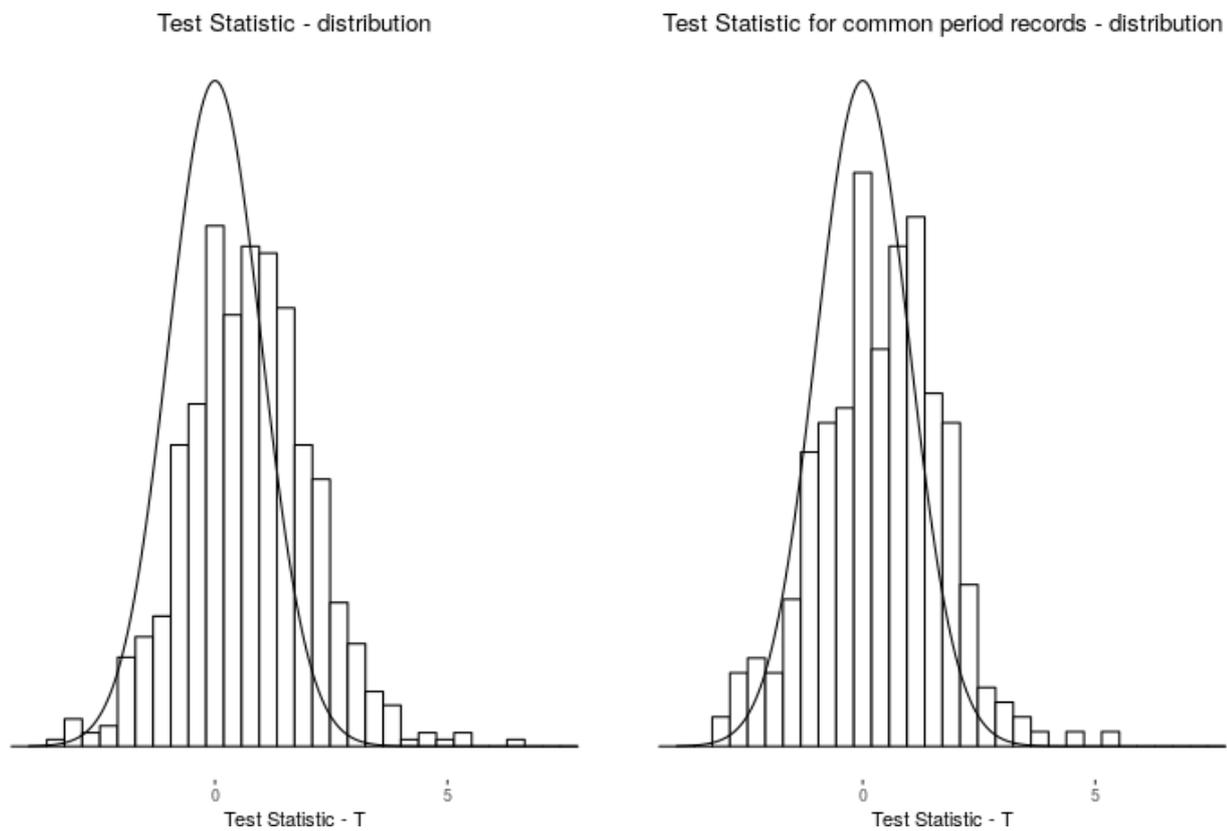
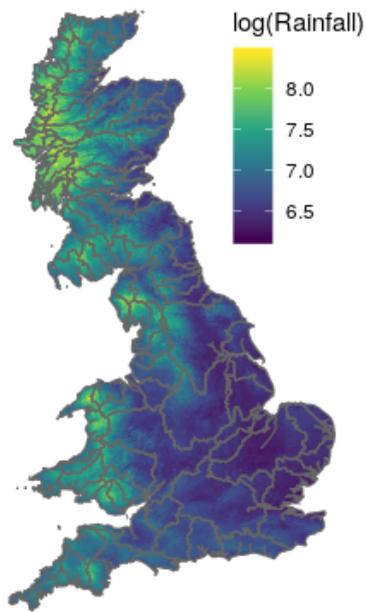
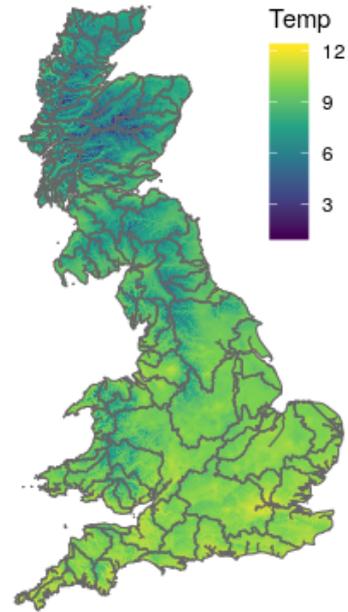


Figure S3. Histogram of the test statistics for all stations and the pdf of the standard normal distribution. Left panel: full dataset; right panel: long common time period (1976-2016) dataset

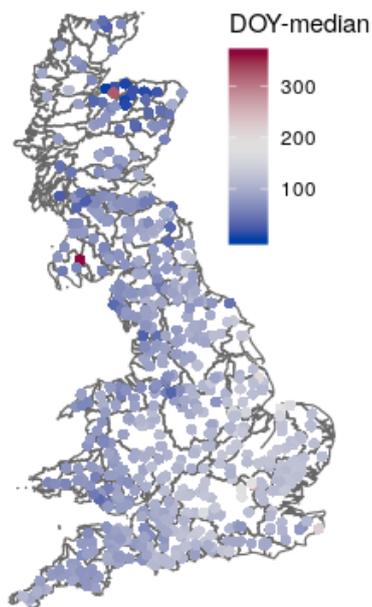
Mean rainfall in mm - log scale (1981-2010)



Mean temperature in °C (1981-2010)



Seasonality of annual maximum flow



Modal month of annual maximum flow

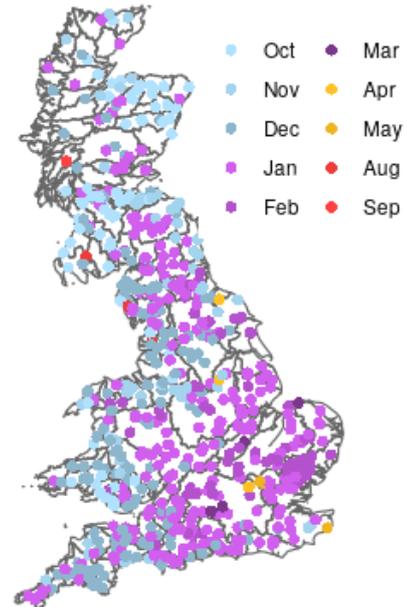


Figure S4. Top left panel: rainfall climatology (1981-2010) - mm, log scale. Top right panel: temperature climatology (1981-2010) - °C. Bottom left panel: seasonality of annual maxima flow, median day of peak flow. Bottom right panel: seasonality of annual maxima flow, modal month of peak flow.

October 22, 2019, 3:53pm

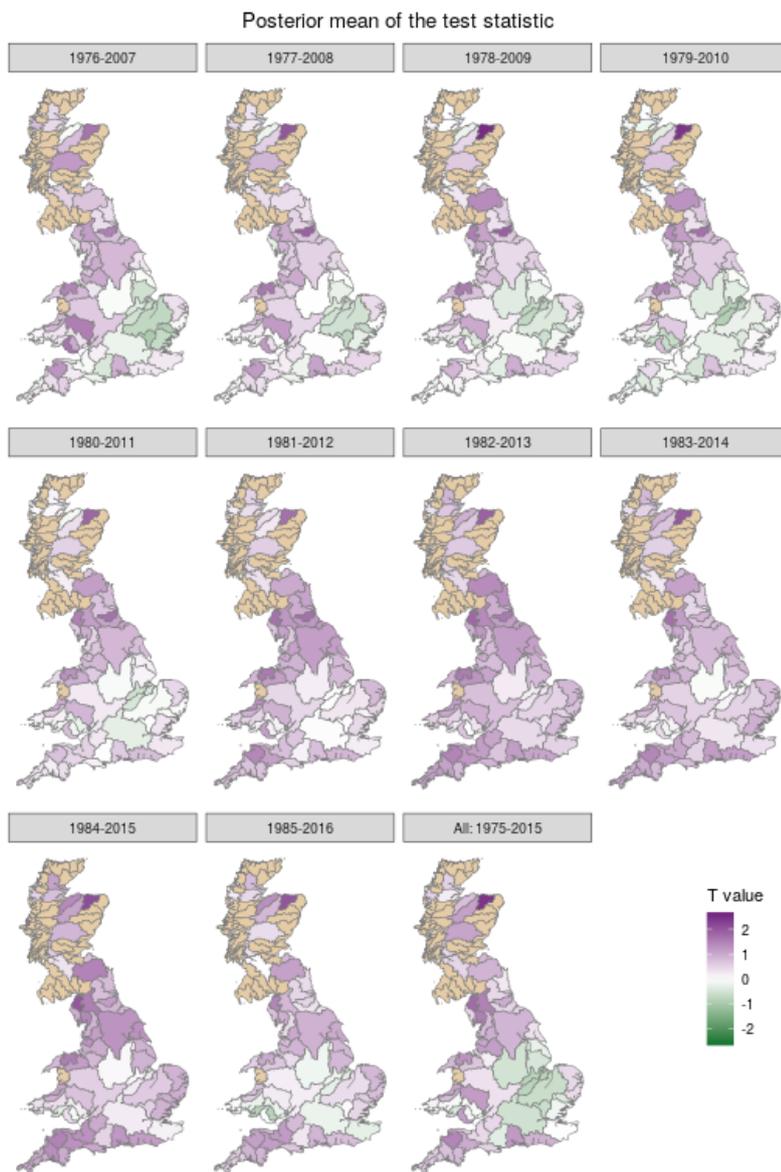


Figure S5. Estimated posterior mean for each area specific test statistic value when using different 31-year long subsets of the data and the 41-year long subset in the period 1976-2016.

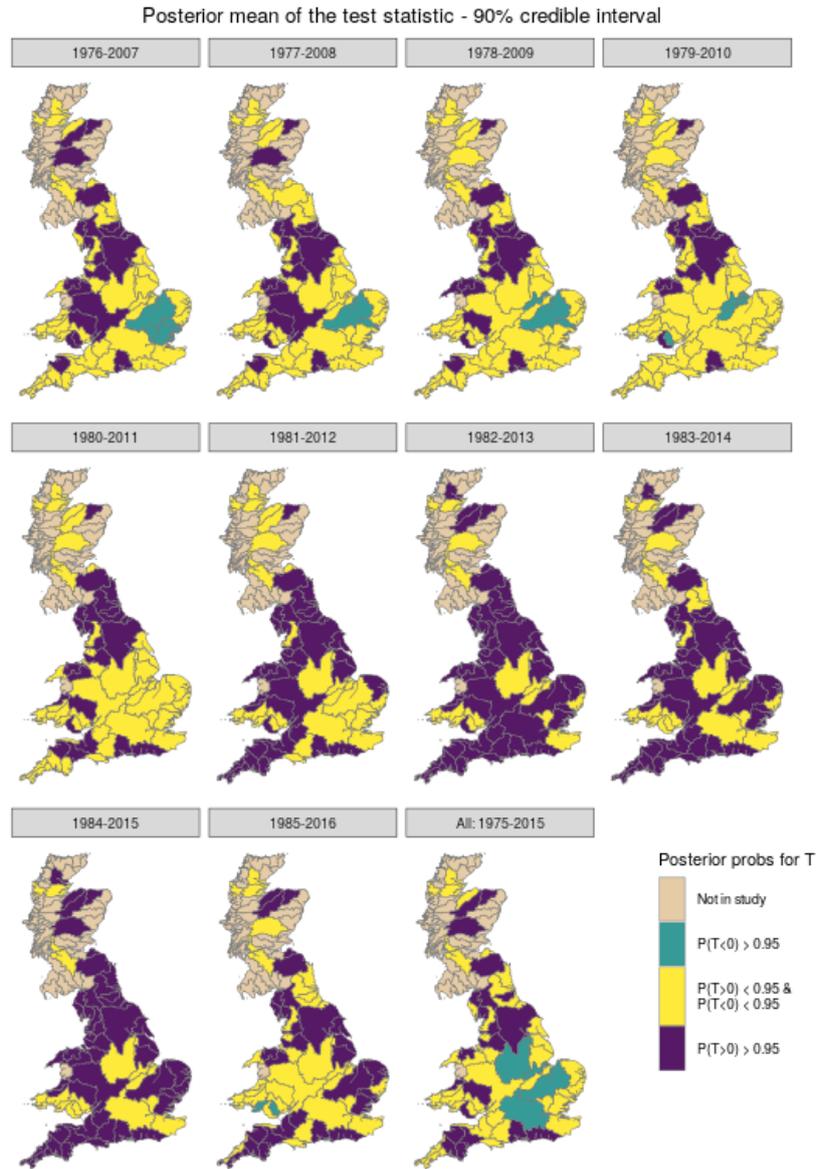


Figure S6. Summarised information for the 90% credible interval of each area specific test statistic value when using different 31-year long subsets of the data and the 41-year long subset in the period 1976-2016.

Table S1. Inference for key parameters in the areal model

	0.025 perc.	0.05 perc.	median	0.95 perc.	0.975 perc.	Mean
μ	0.6144	0.6410	0.7772	0.9142	0.9410	0.7777
σ_T^2	1.3665	1.3911	1.5311	1.6886	1.7200	1.5345
σ_H^2	0.1723	0.1881	0.2979	0.4610	0.4996	0.3077

Table S2. Inference for key parameters in the areal model when using the subset of records with long common time period (1976-2016)

	0.025 perc.	0.05 perc.	median	0.95 perc.	0.975 perc.	Mean
μ	0.2675	0.3076	0.5122	0.7186	0.7595	0.5130
σ_T^2	0.9149	0.9403	1.0894	1.2678	1.3046	1.0950
σ_H^2	0.3812	0.4137	0.6391	0.9764	1.0562	0.6597

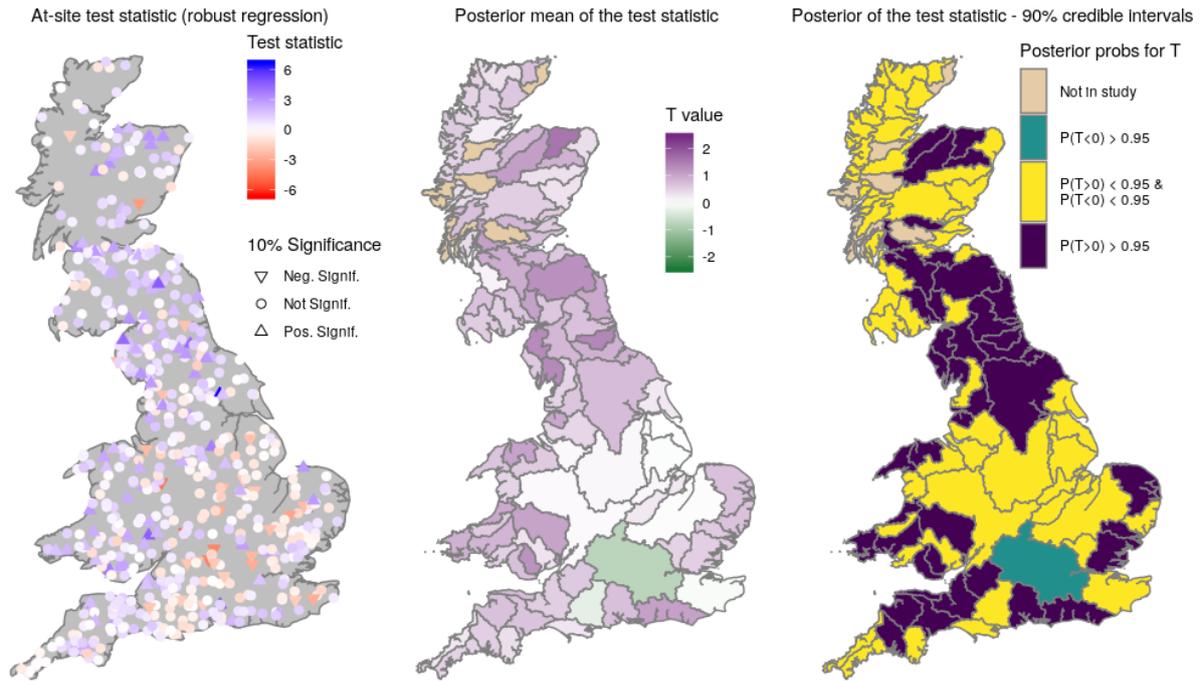


Figure S7. Left panel: at-site test statistic derived using robust regression and significance at 10% significance level for all stations. Central panel: estimated posterior mean derived from the proposed areal model for each area specific test statistic value. Right panel: summarised information for the 90% credible interval for each area specific test statistic value. Test statistics included in the areal model derived using robust regression.

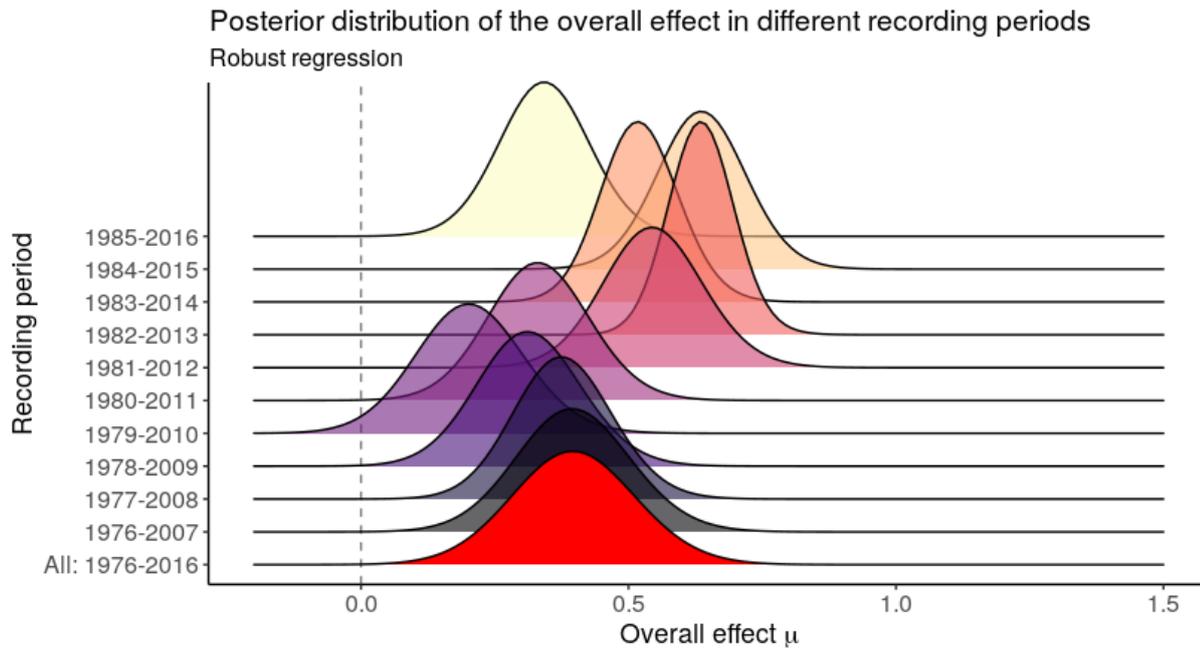


Figure S8. Estimated posterior distributions of μ when using different 31-year long subsets and the 41-year long subset in the period 1976-2016. Test statistics included in the areal model derived using robust regression.

dataPreparation.R

```
library(purrr); library(magrittr)
library(lubridate)
library(rgdal) ## to read spatial data
library(maptools)
library(ggplot2)
library(winFapReader) ## available in github devtools::install_github("ilapros/winFapReader")
## also needed is to have the following packages installed maps, rgeos

options(stringsAsFactors = FALSE)

## according to the NRFA licence agreement the original data used in the analysis can not be shared
- but it can be easily retrieved on their website
## two sets of files are used: peak flow data (from the winFap files) and spatial data

##### peak flow data and catchment descriptors can be downloaded from
##### https://nrfa.ceh.ac.uk/peak-flow-dataset
##### at time of writing this is version 7
##### unzip the downloaded zipped files in a folder so that the "Suitable for Pooling/", "Suitable for
QMED/" and "Not suitable for QMED or Pooling" exist

## this file assumes the directory where the three folders are is called "v70"

## the shapefile of the hydrometric area of the UK can be retrieved at
https://catalogue.ceh.ac.uk/documents/1957166d-7523-44f4-b279-aa5314163237
## choose the options "Whole dataset", output format "Shapefile" and output coordinate reference
system "British National Grid"

## this file assumes that the shapefile are saved in a folder called "hydAreaNRFA"

##### flow data preparation -----

setwd("../v70") ##### change this if the folder with the winFap files is called something else

##### these are the files we will need to read
suitPool <- unlist(strsplit(list.files(path = "./Suitable for Pooling/", pattern = ".AM"),split = ".AM"))
suitQMED <- unlist(strsplit(list.files(path = "./Suitable for QMED//", pattern = ".AM"),split =
".AM"))
suitNO <- unlist(strsplit(list.files(path = "./Not suitable for QMED or Pooling/", pattern =
".AM"),split = ".AM"))

## read every file and stack them on top of each other
## read_amax is a winFapReader function
## solution with purrr is concise (although still not as elegant as it should be)

allAmax <- c(suitPool,suitQMED,suitNO) %>%
  map(function(x) read_amax(x,"./")) %>%
  reduce(rbind)

### any new peaks on 1-October?
```

```

zz <- allAmax[month(allAmax$Date) == 10 & day(allAmax$Date) == 1, ]
### we have 17 knoww events for which the event happened before 9am so is assigned to the WY
before
### are all the 1st Oct event which are known still in the record?
all(zz$Date[year(zz$Date) != zz$WaterYear] %in% winfapReader::known_Oct1$Date)
## yes
### any new records (after 2015 for release from 6 to 7) with date in 1st October?
any(year(zz$Date) > 2015)
## no
rm(zz)

allAmax$Station <- as.numeric(allAmax$Station)
## only keep non-rejected records
allAmax <- allAmax[allAmax$Rejected == FALSE,]
allAmax <- allAmax[order(allAmax$Station,allAmax$WaterYear),]

## similarly read cathchment descriptors with read_cd3

catchDesc <- c(suitPool,suitQMED,suitNO) %>%
  map(function(x) read_cd3(x, ".")) %>%
  reduce(rbind)

catchDesc$Station <- as.numeric(catchDesc$Station)
catchDesc <- catchDesc[order(catchDesc$Station),]

### compute number of valid AMAX years in each station
sumAmax <- as.data.frame(cbind(
  tapply(allAmax$Flow,
    factor(allAmax$Station),
    median),
  tapply(allAmax$Flow,
    factor(allAmax$Station),
    length))); names(sumAmax) <- c("QMED", "N_AM")
sumAmax$Station <- as.numeric(rownames(sumAmax))

## and add this to the catchment descriptors
catchDesc <- merge(catchDesc,sumAmax)

### compute end year of record in all stations
endYear <- data.frame(endYear = tapply(allAmax$WaterYear,
  factor(allAmax$Station),max))
endYear$Station <- as.numeric(rownames(endYear))
## and add this to the catchment descriptors
catchDesc <- merge(catchDesc,endYear)

catchDesc <- catchDesc[order(catchDesc$Station),]

rm(sumAmax, endYear)

## we don't really need catchment descriptors other than the station number and station location
## so drop most of them

```

```

catchDesc <-
catchDesc[,c("Station","Easting","Northing","Grid","DTM_Area","SAAR","BFIHOST","URBEXT
2000","suitQMED","suitPool","QMED","N_AM","endYear")]

#### needed in the spatial analys: hydrometric area, which can be derived from the first two digits
the station number
ha <- as.character(catchDesc$Station)
ha <- ifelse(nchar(ha) == 4,paste0("0",ha),ha) ## stations in hyd_area < 10 are 4 char long
ha <- ifelse(nchar(ha) == 5,paste0("0",ha),ha) ## stations in hyd_area > 99 are 6 char long
#### now all station number are 6 char long - with the first 3 characters indicating the hyd_area
ha <- as.numeric(substr(ha,1,3))
catchDesc$hyd_area <- ha; rm(ha)

### now select only stations in continental GB and with suitable quality
### exclude stations which are heavily urban, short (in AMAX records) and which end in 20th
century
subStat <- catchDesc[catchDesc$suitQMED == "YES" & ## deemed of good enough quality by
NRFA
      catchDesc$URBEXT2000 < 0.1 & ## take out heavy urbanised catchments
      catchDesc$Grid == "GB" & ## GB only
      catchDesc$N_AM > 20 &
      catchDesc$endYear > 2000 ,"Station"] ## record with more than 20 years of data

amaxVals <- allAmax[(allAmax$Station %in% subStat) &
      (allAmax$Rejected == FALSE),] ## remove rejected AMAX values
## summary(catchDesc[catchDesc$Station %in% subStat,"N_AM"]) ## OK

#### standardise Water Year to 0-1 across all station
#### THIS DOES NOT CHANGE THE TEST STATISTIC VALUE
amaxVals$sWY <-
(amaxVals$WaterYear-min(amaxVals$WaterYear)+0.01)/(diff(range(amaxVals$WaterYear))+0.02)
## attach information on the hydrometric area to which the station belong
amaxVals <- merge(amaxVals,catchDesc[,c("Station","hyd_area")])

amaxVals <- amaxVals[amaxVals$Flow > 10^{-6},] # there is a 0 value at station 44013 - drop it
as it seems unlikely to be true

#### amaxVals is the final annual maxima record used in the analysis

#### what we actually use is the test statistioc of the linear model fitted to the log(Flow) of each
station

getTforLN<-function(x){
  x <-
  zz <- summary(lm(log(x$Flow)~x$sWY))
  as.numeric(c(zz$coef[,1], zz$coef[,2],zz$coef[2,3],zz$sigma))
}
TstatLN <- do.call(what = rbind,by(amaxVals,amaxVals$Station,getTforLN))
TstatLN <- cbind(Station = as.numeric(rownames(TstatLN)), TstatLN)
colnames(TstatLN ) <- c("Station","mu","mu1","mu_se","mu1_se","mu1_T","sigma")
TstatLN <- merge(as.data.frame(TstatLN), catchDesc)

```

```

TstatLN <- TstatLN[order(TstatLN$hyd_area,TstatLN$Station),]

getSubSel <- tapply(amaxVals$WaterYear[amaxVals$Rejected == FALSE],
  amaxVals$Station[amaxVals$Rejected == FALSE],
  function(x) length(x[x %in% seq(1976,2016)]) == 41)
longcommYearsSel <- amaxVals[(amaxVals$Station %in% names(which(getSubSel))) &
(amaxVals$WaterYear %in% seq(1976,2016)),]

lcomTstat <- do.call(what = rbind,by(longcommYearsSel,longcommYearsSel$Station,getTforLN))
lcomTstat <- cbind(Station = as.numeric(rownames(lcomTstat)), lcomTstat)
colnames(lcomTstat ) <-
c("Station","commu","commu1","commu_se","commu1_se","commu1_T","comsigma")
lcomTstat <- merge(as.data.frame(lcomTstat),catchDesc)
lcomTstat <- lcomTstat[order(lcomTstat$hyd_area,lcomTstat$Station),]

TstatLN$fhydarea <- factor(TstatLN$hyd_area)
lcomTstat$fhydarea <- factor(lcomTstat$hyd_area)

## fit 10 models for windows of 31 years of data
getTonly<-function(x){
  zz <- summary(lm(log(x$Flow)~x$sWY)) ### /sd(log(x$Flow))
  as.numeric(c(zz$coef[2,3]))
}

# ## calculate Test statistics on data between firstYear:(firstYear+totYear)
builtTstatYears <- function(dat, firstYear, totYears){
  dat <- dat[order(dat$Station),]
  j <- 0
  out <- data.frame(Station = unique(dat$Station))
  while(max(dat$WaterYear) >= (firstYear+totYears+j-1)){
    tt <- dat[dat$WaterYear >= (firstYear+j) & (dat$WaterYear < (firstYear+totYears+j)),]
    o1 <- data.frame(o1 = as.vector(by(tt,tt$Station,getTonly)))
    colnames(o1) <- paste0("mu1_T_",(firstYear+j))
    out <- cbind(out,o1)
    j <- j+1
  }
  out
}

# ## Create a "moving inference" for the last 10 years
zz <- builtTstatYears(longcommYearsSel,1976,32)
longTstats <- merge(lcomTstat,zz)
longTstats <- longTstats[order(longTstats$hyd_area,longTstats$Station),]#; rm(zz)

mlong <- tidyr::gather(longTstats[,c("Station",grep("mu1_T",x = names(longTstats),value =
TRUE),"Easting","Northing")],
  key = timeSpan, value = mu1T, 2:12)

```

```

### robust regression
library(robust)

getTforRobLN<-function(x){
  zz <- summary(lmRob(log(x$Flow)~x$sWY, control = lmRob.control(mxr = 100, mxl = 100, mxs
= 100), setting = "KS2014"))
  as.numeric(c(zz$coef[,1], zz$coef[,2],zz$coef[2,3],zz$sigma))
}
TstatRobLN <- do.call(what = rbind,by(amaxVals,amaxVals$Station,getTforRobLN))
TstatRobLN <- cbind(Station = as.numeric(rownames(TstatRobLN)), TstatRobLN)
colnames(TstatRobLN ) <- c("Station","rmu","rmu1","rmu_se","rmu1_se","rmu1_T","rsigma")
TstatRobLN <- merge(as.data.frame(TstatRobLN), catchDesc)
TstatRobLN <- TstatRobLN[order(TstatRobLN$hyd_area,TstatRobLN$Station),]

lcomTRstat <- do.call(what = rbind,
by(longcommYearsSel,longcommYearsSel$Station,getTforRobLN))
lcomTRstat <- cbind(Station = as.numeric(rownames(lcomTRstat)), lcomTRstat)
colnames(lcomTRstat ) <-
c("Station","rcommu","rcommu1","rcommu_se","rcommu1_se","rcommu1_T","rcomsigma")
lcomTRstat <- merge(as.data.frame(lcomTRstat),catchDesc)
lcomTRstat <- lcomTRstat[order(lcomTRstat$hyd_area,lcomTRstat$Station),]

getTforRobLN<-function(x){
  zz <- summary(lmRob(log(x$Flow)~x$sWY, control = lmRob.control(mxr = 100, mxl = 100, mxs
= 100)))
  zz$coef[2,3]
}

# ## calculate Test statistics on data between firstYear:(firstYear+totYear)
builtTRobstatYears <- function(dat, firstYear, totYears){
  dat <- dat[order(dat$Station),]
  j <- 0
  out <- data.frame(Station = unique(dat$Station))
  while(max(dat$WaterYear) >= (firstYear+totYears+j-1)){
    tt <- dat[dat$WaterYear >= (firstYear+j) & (dat$WaterYear < (firstYear+totYears+j)),]
    o1 <- data.frame(o1 = as.vector(by(tt,tt$Station,getTforRobLN)))
    colnames(o1) <- paste0("rmu1_T_",(firstYear+j))
    out <- cbind(out,o1)
    j <- j+1
  }
  out
}

# ## Create a "moving inference" for the last 10 years
zz <- builtTRobstatYears(longcommYearsSel,1976,32)
longRTstats <- merge(lcomTRstat,zz)
longRTstats$fhydarea <- factor(longRTstats$hyd_area)

```

```
longRTstats <- longRTstats[order(longRTstats$hyd_area,longRTstats$Station),]#; rm(zz)
```

```
mRlong <- tidyr::gather(longRTstats[,c("Station",grep("rmu1_T",x = names(longRTstats),value = TRUE),"Easting","Northing")],  
  key = timeSpan, value = rmu1T, 2:12)
```

```
##### create the seasonality index for river stasjon
```

```
amaxVals$doy <- as.numeric(  
  lubridate::ymd(amaxVals$Date) -  
  lubridate::ymd(paste0(amaxVals$WaterYear,"-10-01"))+1)  
### some cases of values == 366 are not due to leap years  
### but to events happening before 9 am on 1st October  
amaxVals[amaxVals$doy==366 & (!lubridate::leap_year(amaxVals$WaterYear + 1)),"doy"] <- 1
```

```
amaxVals$month <- as.numeric(lubridate::month(amaxVals$Date)) - 9  
amaxVals$month <- ifelse(amaxVals$month > 0, amaxVals$month, amaxVals$month+12)
```

```
getThetaMedian <- function(x) {  
  tt2 <- as.numeric(median(circular::conversion.circular(x*(2*pi)/366))) * 366/(2*pi)  
  # ifelse(sign(tt2) == 1, 0, 183) + abs(tt2)  
  abs(- tt2 - ifelse(sign(tt2) == 1, 0, 366))  
}  
xxd <- tapply(amaxVals$doy,factor(amaxVals$Station),  
  getThetaMedian)  
xxd <- xxd[order(as.numeric(names(xxd)))]  
catchDesc <- merge(catchDesc, data.frame(Station = names(xxd), seas = as.numeric(xxd)))
```

```
### now modal month
```

```
xxd <- tapply(amaxVals$month,factor(amaxVals$Station),  
  function(x) as.numeric(names(which.max(table(x))))))  
xxd <- xxd[order(as.numeric(names(xxd)))]  
catchDesc <- merge(catchDesc, data.frame(Station = names(xxd), modeMonth = as.numeric(xxd)))
```

```
save(list = c("TstatLN","lcomTstat","lcomTRstat","catchDesc",  
  "TstatRobLN", "amaxVals","longcommYearsSel",  
  "longTstats","longRTstats","mRlong","mlong"),  
  file = "../flowData2.RData")
```

```
##### spatial data preparation -----
```

```
##### this is a bit slow  
setwd("../")
```

```
hyd_areas <- readOGR(dsn = "../hydAreaNRFA", layer = "hyd_areas")  
hyd_areas$HA_NUM <- as.numeric(as.character(hyd_areas$HA_NUM))  
hyd_areas <- hyd_areas[hyd_areas$HA_NUM < 100,]  
hyd_areas.dat <- hyd_areas@data
```

```

### this is what will be used to do the maps
hyd.areas.f <- fortify(hyd.areas, region = "HA_NUM")
hyd.areas.f$HA_NUM <- as.integer(hyd.areas.f$id)

### to avoid overcrowding some plots derive a shapefile of Britain which is detailed but doesn't
have all the hydrometric areas
proj4string(hyd.areas) <- CRS("+init=epsg:27700")
hyd.areas.f <- hyd.areas.f[hyd.areas.f$long > 120000,]

UK <- map_data(map = "world", region = "UK")
GB <- UK[UK$subregion == "Great Britain",c("long","lat","order")]
GB <- SpatialPolygons(Srl = list(Polygons(list(Polygon(coords = GB[,c("long","lat")])),ID =
"one")),
    pO = as.integer(1), proj4string = CRS("+proj=longlat"))
GB <- spTransform(GB,CRS("+init=epsg:27700"))
GB <- rgeos::gIntersection(hyd.areas, GB) ## make it look like the more detailed map - SLOW

##### downloaded from https://gadm.org/download_country_v3.html
##### download the UK shapefile
##### saved in mapppingShp folder
### this is needed to make the map of countries/nations across GB (Wales, Scotland, England)
gbadm <- readOGR(dsn = "mappingShp/",
    layer = "gadm36_GBR_2")
gbadm <- gbadm[!gbadm$NAME_1 %in% "Northern Ireland",]
gbadm <- gbadm[!gbadm$NAME_2 %in% c("Shetland Islands","Orkney Islands","Eilean Siar"),]

gbadm <- spTransform(x = gbadm, CRSobj = CRS("+init=epsg:27700"))
gbadm <- raster::intersect(GB, gbadm)
gbadm$Country <- "England"
gbadm$Country[gbadm$NAME_1 == "Scotland"] <- "Scotland"
gbadm$Country[gbadm$NAME_1 == "Wales"] <- "Wales"
gbadm <- raster::intersect(hyd.areas, gbadm)

#plot(gbadm)

gbadm.f <- fortify(gbadm, region = "Country")

GB <- fortify(GB); rm(UK)

save(list = c("hyd.areas.f","gbadm.f","hyd.areas","GB"), file = "spatialObjs2.RData")

# sessionInfo()
# R version 3.6.1 (2019-07-05)
# Platform: x86_64-pc-linux-gnu (64-bit)
# Running under: Ubuntu 18.04.3 LTS
#
# Matrix products: default
# BLAS: /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.7.1
# LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.7.1

```

```
#
# locale:
# [1] LC_CTYPE=en_GB.UTF-8    LC_NUMERIC=C            LC_TIME=en_GB.UTF-8
# [4] LC_COLLATE=en_GB.UTF-8 LC_MONETARY=en_GB.UTF-8
LC_MESSAGES=en_GB.UTF-8
# [7] LC_PAPER=en_GB.UTF-8   LC_NAME=C              LC_ADDRESS=C
# [10] LC_TELEPHONE=C        LC_MEASUREMENT=en_GB.UTF-8
LC_IDENTIFICATION=C
#
# attached base packages:
# [1] stats  graphics grDevices utils  datasets methods base
#
# other attached packages:
# [1] robust_0.4-18.1  fit.models_0.5-14  winfapReader_0.1.0  ggplot2_3.2.1
# [5] maptools_0.9-5  rgdal_1.4-3        sp_1.3-1            lubridate_1.7.4
# [9] magrittr_1.5    purrr_0.3.2
#
# loaded via a namespace (and not attached):
# [1] pcaPP_1.9-73    Rcpp_1.0.2        circular_0.4-93    DEoptimR_1.0-8    pillar_1.4.2
# [6] compiler_3.6.1  tools_3.6.1       boot_1.3-20        zeallot_0.1.0     tibble_2.1.3
# [11] lifecycle_0.1.0  gtable_0.3.0     lattice_0.20-38    pkgconfig_2.0.2   rlang_0.4.0
# [16] rstudioapi_0.10  yaml_2.2.0        mvtnorm_1.0-10     cluster_2.1.0     withr_2.1.2
# [21] dplyr_0.8.3     stringr_1.4.0     vctrs_0.2.0       stats4_3.6.1      grid_3.6.1
# [26] tidyselect_0.2.5  robustbase_0.93-5  glue_1.3.1         rrcov_1.4-7       R6_2.4.0
# [31] foreign_0.8-71   tidyr_1.0.0       MASS_7.3-51.1     ellipsis_0.2.0.1  scales_1.0.0
# [36] backports_1.1.4  assertthat_0.2.1  colorspace_1.4-1  stringi_1.4.3     lazyeval_0.2.2
# [41] munsell_0.5.0    crayon_1.3.4
```

dataAnalysisAndFigures.R

```
## ----setup, echo=FALSE,eval=TRUE,cache=FALSE-----
knitr::opts_chunk$set(message = FALSE, warning =
FALSE,echo=FALSE,cache=TRUE,dev="png")
options(stringsAsFactors = FALSE) # # as always...
library(knitr); library(gridExtra); library(sp); library(raster)
library(latex2exp);suppressMessages(library(ggirdges)); library(scales)
suppressMessages(library(ggplot2)); suppressMessages(library(viridis)); library(colorspace)
## installation of INLA can be done via
## install.packages("INLA", repos=c(getOption("repos")),
INLA="https://inla.r-inla-download.org/R/stable"), dep=TRUE)
suppressPackageStartupMessages(library(INLA))
```

```
### later in the analysis a function from tidyr is used
### check if the library is installed
("tidyr" %in% installed.packages()[,1])
```

```
### load in data
### these are derived in the dataPreparation.R file
load("spatialObjs2.RData")
load("flowData2.RData")
```

```
##custom ggplot theme used to make maps look pretty
map_theme <- function () {
  theme_bw() %+replace%
  theme(legend.position = c(.79, .76),# legend.box = "horizontal",
  axis.title=element_blank(), axis.text=element_blank(),
  axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
  panel.grid.major = element_blank(),
  panel.border = element_blank(),panel.grid.minor = element_blank())
}
```

```
## slightly different location of legend
map_themeH <- function () {
  theme_bw() %+replace%
  theme(legend.position = c(.79, .81),# legend.box = "horizontal",
  axis.title=element_blank(), axis.text=element_blank(),
  axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
  panel.grid.major = element_blank(),
  panel.border = element_blank(),panel.grid.minor = element_blank())
}
```

```
map_themeH2 <- function () {
  theme_bw() %+replace%
  theme(legend.position = c(.86, .78),# legend.box = "horizontal",
```

```

axis.title=element_blank(), axis.text=element_blank(),
axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
panel.grid.major = element_blank(),
panel.border = element_blank(),panel.grid.minor = element_blank()

}

## ----inlaMOdIID, echo=FALSE-----
## the first areal model fitted to the whole dataset
taug <- TstatLN[,c("hyd_area","fhydarea","mu1_T")]
taug <- rbind(taug, data.frame(hyd_area = unique(TstatLN$hyd_area), fhydarea =
unique(TstatLN$fhydarea), mu1_T = NA))
mod_iid_hyd<-inla(mu1_T~f(fhydarea, model="iid",
hyper = list(prec = list(prior="pc.prec", param = c(1.5, 0.01))),
control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link
= 1), data=taug)
muci <- inla.qmarginal(c(0.05,0.95), mod_iid_hyd$marginals.fixed$(Intercept), len = 2048L)

## ----figINLAIid, fig.width=10.4, fig.asp=0.6, fig.cap="Left map: at-site test statistic and
significance at 90% level for all stations. Central map: estimated posterior mean for each area
specific test statistic value. Right map: summarised information for the 90% credible interval for
each area specific test statistic value.",echo=FALSE,eval=TRUE,cache=TRUE----
## Figure 1
tdat <- data.frame(fhydarea = factor(seq(1,97)))
tdat <- merge(tdat, data.frame(fhydarea = taug$fhydarea[(nrow(TstatLN)+1):(nrow(taug))],
postRE =
mod_iid_hyd$summary.random$fhydarea$mean[match(mod_iid_hyd$summary.random$fhydarea$
ID,
taug$fhydarea[(nrow(TstatLN)+1):
(nrow(taug))]]),
postT = mod_iid_hyd$summary.fitted.values$mean[(nrow(TstatLN)+1):
(nrow(taug))],
postTsd = mod_iid_hyd$summary.fitted.values$sd[(nrow(TstatLN)+1):
(nrow(taug))],
postREp = as.vector(unlist(lapply(
mod_iid_hyd$marginals.random$fhydarea,function(x)
inla.pmarginal(0,marginal = x))))),
postTp = as.vector(mod_iid_hyd$summary.fitted.values$`0 cdf`[(nrow(TstatLN)
+1):(nrow(taug))]),
all.x=TRUE)
tdat$HA_NUM <- as.numeric(as.character(tdat$fhydarea))
tdat$postT[is.na(tdat$postT)] <- NA_real_; tdat$postTsd[is.na(tdat$postTsd)] <- NA_real_
tdat$postREp[is.na(tdat$postREp)] <- NA_real_; tdat$postTp[is.na(tdat$postTp)] <- NA_real_
tdat$sigRE <- ifelse(is.na(tdat$postREp),"Not in study","Not Sign.")
tdat$sigT <- ifelse(is.na(tdat$postTp),"Not in study","Not Sign.");
tdat$sigRE[tdat$postREp < .05] <- "Positive"; tdat$sigRE[tdat$postREp > .95] <- "Negative"
tdat$sigT[tdat$postTp < .05] <- "Positive"; tdat$sigT[tdat$postTp > .95] <- "Negative"
nneut <- sum(tdat$sigT == "Not Sign."); npos <- sum(tdat$sigT == "Positive"); nneg <-
sum(tdat$sigT == "Negative")
tdat$sigRE <- factor(tdat$sigRE,levels = c("Not in study","Negative","Not Sign.,"Positive"))
tdat$sigT <- factor(tdat$sigT,levels = c("Not in study","Negative","Not Sign.,"Positive"))
hlab <- c("\n Not in study \n ", "\n P(h<0) > 0.95 \n ",

```

```

" \n P(h>0) < 0.95 & \n P(h<0) < 0.95 \n ", " \n P(h>0) > 0.95 \n ") [c("Not in
study", "Negative", "Not Sign.", "Positive")] %in% unique(tdat$SIGRE)]
tlab <- c(" \n Not in study \n ", " \n P(T<0) > 0.95 \n ",
" \n P(T>0) < 0.95 & \n P(T<0) < 0.95 \n ", " \n P(T>0) > 0.95 \n ") [c("Not in
study", "Negative", "Not Sign.", "Positive")] %in% unique(tdat$SIGT)]
tdat <- merge(hyd.areas.f, tdat)

## map of at-site tests
p1 <- ggplot(TstatLN[!is.na(TstatLN$Easting),]) +
  geom_polygon(data=GB,
    aes(long, lat, group=group), fill=rgb(.75,.75,.75), color="grey50")+
  geom_point(aes(x=Easting, y=Northing,
    pch=cut(mu1_T, qnorm(c(1/10^15, 0.05, .95, 1-1/10^15))),
    col=mu1_T, fill=mu1_T), size=2.3) +
  scale_shape_manual(name="10% Significance", values=c(25, 21, 24),
    labels=c("Neg. Signif.", "Not Signif.", "Pos. Signif.)) +
  scale_colour_gradient2(name="Test statistic", low="#FF0000",
    high="#0000FF", limits=c(-6.6, 6.6)) +
  scale_fill_gradient2(name="Test statistic", low="#FF0000",
    high="#0000FF", limits=c(-6.6, 6.6)) +
  ggtitle("At-site test statistic") + coord_equal() +
  theme_bw() %+replace%
  theme(legend.position=c(.86, .76), # legend.box="horizontal",
    axis.title=element_blank(), axis.text=element_blank(),
    axis.ticks=element_blank(), plot.title=element_text(hjust=0.5),
    panel.grid.major=element_blank(),
    panel.border=element_blank(), panel.grid.minor=element_blank()) +
  guides(fill=guide_colourbar(order=1), shape=guide_legend(order=2), color=FALSE)

## mean areal test statistic
p2 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group, fill=postT), color="grey50")+
  scale_fill_gradient2(name="T value", na.value=rgb(.9,.8,.65), low="#1b7837",
    high="#762a83", limits=c(-2.45, 2.45)) +
  ggtitle(TeX("Posterior mean of the test statistic")) + map_theme() + coord_equal()

## categorical credi int sign for areal test statistic
p3 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group, fill=sigT), color="grey50")+
  scale_fill_manual(values=c("Negative"="#21908CE6", "Not Sign."="#FDE725E6",
    "Positive"="#440154E6", "Not in study"=rgb(.9,.8,.65)),
    labels=tlab, name="Posterior probs for T") +
  ggtitle(TeX("Posterior of the test statistic - 90% credible intervals")) +
  map_themeH() + coord_equal()

grid.arrange(p1, p2, p3, ncol=3)
rm(p1, p2, p3)

## ----lcommoninlaMdiID, echo=FALSE-----
## the second areal model fitted to the long common period dataset
ltaug <- lcomTstat[,c("hyd_area", "fhydarea", "commu1_T")]
ltaug <- rbind(ltaug, data.frame(hyd_area = unique(lcomTstat$hyd_area), fhydarea =
  unique(lcomTstat$fhydarea), commu1_T = NA))

```

```

lcom_mod_iid_hyd<-inla(commu1_T~f(fhydarea, model="iid"),
  control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link =
1), data=ltaug)
lmuci <- inla.qmarginal(c(0.05,0.95), lcom_mod_iid_hyd$marginals.fixed$(Intercept), len =
2048L)

## ----lcommonfigINLAiid, fig.width=10.4, fig.asp=0.6, fig.cap="Results for a long common time
period analysis (1976-2016). Left map: at-site test statistic values and significance at 90% level for
all stations. Central map: estimated posterior mean for each area specific test statistic value. Right
map: summarised information for the 90% credible interval for each area specific test statistic
value.",cache=TRUE,eval=TRUE,echo=FALSE----
## Figure 2
tdat <- data.frame(fhydarea = factor(seq(1,97)))
tdat <- merge(tdat, data.frame(fhydarea = ltaug$fhydarea[(nrow(lcomTstat)+1):(nrow(ltaug))],
  postRE = lcom_mod_iid_hyd$summary.random$fhydarea[,2],
  postT = lcom_mod_iid_hyd$summary.fitted.values$mean[(nrow(lcomTstat)+1):
(nrow(ltaug))],
  postTsd = lcom_mod_iid_hyd$summary.fitted.values$sd[(nrow(lcomTstat)+1):
(nrow(ltaug))],
  postREp = as.vector(
  unlist(lapply(lcom_mod_iid_hyd$marginals.random$fhydarea,
  function(x) inla.pmarginal(0,marginal = x))),
  postTp = as.vector(
  lcom_mod_iid_hyd$summary.fitted.values$`0 cdf`[(nrow(lcomTstat)+1):
(nrow(ltaug))])),
  all.x=TRUE)
tdat$HA_NUM <- as.numeric(as.character(tdat$fhydarea))
tdat$postT[is.na(tdat$postT)] <- NA_real_; tdat$postTsd[is.na(tdat$postTsd)] <- NA_real_
tdat$postREp[is.na(tdat$postREp)] <- NA_real_; tdat$postTp[is.na(tdat$postTp)] <- NA_real_
tdat$sigRE <- ifelse(is.na(tdat$postRE), "Not in study", "Not Sign."); tdat$sigT <-
ifelse(is.na(tdat$postT), "Not in study", "Not Sign.");
tdat$sigRE[tdat$postREp < .05] <- "Positive"; tdat$sigRE[tdat$postREp > .95] <- "Negative"
tdat$sigT[tdat$postTp < .05] <- "Positive"; tdat$sigT[tdat$postTp > .95] <- "Negative"
tdat$sigRE <- factor(tdat$sigRE,levels = c("Not in study","Negative","Not Sign.,"Positive"))
tdat$sigT <- factor(tdat$sigT,levels = c("Not in study","Negative","Not Sign.,"Positive"))
nneut <- sum(tdat$sigT == "Not Sign."); npos <- sum(tdat$sigT == "Positive"); nneg <-
sum(tdat$sigT == "Negative")
nmneg <- sum(tdat$postT[!is.na(tdat$postT)] <0)
tlab <- c("\n Not in study \n ", "\n P(T<0) > 0.95 \n ",
  "\n P(T>0) < 0.95 & \n P(T<0) < 0.95 \n ", "\n P(T>0) > 0.95 \n ")[c("Not in
study","Negative","Not Sign.,"Positive") %in% unique(tdat$sigT)]
tdat <- merge(hyd.areas.f,tdat)

p2 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group,fill=sigT),color="grey50")+
  scale_fill_manual(values=c("Negative"="#21908CFF", "Not Sign."="#FDE725FF",
  "Positive"="#440154FF", "Not in study"=rgb(.9,.8,.65)),
  labels = tlab, name="Posterior probs for T") +
  ggtitle(TeX("Posterior of the test statistic - 90% credible intervals")) +
  map_themeH() + coord_equal()

p3 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group,fill=postT),color="grey50")+

```

```

scale_fill_gradient2(name="T value", na.value=rgb(.9,.8,.65), low = "#1b7837",
  high = "#762a83", limits = c(-2.45,2.45)) +
ggtitle(TeX("Posterior mean of the test statistic")) + map_theme() + coord_equal()
## at site test statistics
p4 <- ggplot(lcomTstat[!is.na(lcomTstat$Easting),]) +
  geom_polygon(data=GB,aes(long, lat, group=group),fill=rgb(.75,.75,.75),color="grey50")+
  geom_point(aes(x=Easting,y=Northing,
    col=commu1_T,pch=cut(commu1_T,c(-50,-1.64,1.64,50)), fill=commu1_T),size=2.3) +
  scale_shape_manual(name="10% Significance",values=c(25,21,24),
    labels=c("Neg. Signif.", "Not Signif.", "Pos. Signif.)) +
  scale_colour_gradient2(name = "Test statistic", low = "#FF0000",
    high = "#0000FF", limits = c(-6.6,6.6)) +
  scale_fill_gradient2(name = "Test statistic", low = "#FF0000",
    high = "#0000FF", limits = c(-6.6,6.6)) +
  ggtitle("At-site test statistic") + coord_equal() +
  theme_bw() %+replace%
  theme(legend.position = c(.86, .76),# legend.box = "horizontal",
    axis.title=element_blank(), axis.text=element_blank(),
    axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
    panel.grid.major = element_blank(),
    panel.border = element_blank(),panel.grid.minor = element_blank()) +
  guides(fill = guide_colourbar(order=1), shape = guide_legend(order=2),color=FALSE)

grid.arrange(p4,p3,p2,ncol=3)

## ----makeMovingInference, echo = FALSE,cache=TRUE-----

# ## at site tests for each time slice
# ggplot(data=mlong) + geom_point(aes(x=Easting,y=Northing,col=mu1T)) +
# scale_color_viridis()+ facet_wrap(~timeSpan) + theme_bw()
#fixed = cbind(data.frame(timeSpan="all"),lcom_mod_iid_hyd$summary.fixed)
#random = cbind(data.frame(timeSpan="all"),lcom_mod_iid_hyd$summary.random$fhydarea)
#marghyper =
cbind(data.frame(timeSpan="all"),lcom_mod_iid_hyd$marginals.hyperpar$`Precision for
fhydarea`)
margfix = cbind(data.frame(timeSpan="all"),lcom_mod_iid_hyd$marginals.fixed$`(Intercept)`)
hyper = cbind(data.frame(timeSpan="all"),lcom_mod_iid_hyd$summary.hyperpar)
fitted = data.frame(timeSpan="all",
  ID = lcom_mod_iid_hyd$summary.random$fhydarea$ID,
  fitted = lcom_mod_iid_hyd$summary.fitted.values$mean[(nrow(lcomTstat)+1):
(nrow(ltaug))],
  fp = lcom_mod_iid_hyd$summary.fitted.values$`0 cdf`[(nrow(lcomTstat)+1):
(nrow(ltaug))])

#allSubmodels <- list()
for(j in grep("T_19",names(longTstats),value = TRUE)){
  tt <- longTstats[,c("fhydarea",j)]; names(tt)[2] <- "muT"
  tt <- rbind(tt,data.frame(fhydarea = ltaug$fhydarea[(nrow(lcomTstat)+1):(nrow(ltaug))],
muT=NA))
  tout<-inla(muT~f(fhydarea, model="iid"),
    control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link = 1),
data=tt)

```

```

margfix = rbind(margfix,cbind(data.frame(timeSpan=j),tout$marginals.fixed$(Intercept)))
fitted = rbind(fitted, cbind(data.frame(timeSpan=j,
                                     ID = tout$summary.random$fhydarea$ID,
                                     fitted = tout$summary.fitted.values$mean[(nrow(lcomTstat)+1):
(nrow(ltaug))]),
                                     fp = tout$summary.fitted.values$`0 cdf`[(nrow(lcomTstat)+1):
(nrow(ltaug))])))
## not used for final figures in paper
## these extract other useful quantities to look at to compare the pregressive change of the fitted
model
# fixed = rbind(fixed,cbind(data.frame(timeSpan=j),tout$summary.fixed))
# random = rbind(random,cbind(data.frame(timeSpan=j),tout$summary.random$fhydarea))
# marghyper = rbind(marghyper,cbind(data.frame(timeSpan=j),tout$marginals.hyper$`Precision
for fhydarea`))
# hyper = rbind(hyper, cbind(data.frame(timeSpan=j),tout$summary.hyper))
}

inlaAcrossTheYears <- list(fitted=fitted, margfix=margfix)#, marghyper=marghyper,fixed = fixed,
random = random, hyper = hyper, )
inlaAcrossTheYears$margfix$When <- paste(
  substr(as.character(inlaAcrossTheYears$margfix$timeSpan),7,11),
  as.numeric(substr(as.character(inlaAcrossTheYears$margfix$timeSpan),7,11))+31,sep="-")
inlaAcrossTheYears$margfix$When[inlaAcrossTheYears$margfix$When == "-NA"] <- "All: 1976-
2016"
rm(fitted,margfix,tt,j,tout) #fixed,random,hyper,marghyper)

## ----muacrossTheYears,fig.width=8.5, fig.asp=.55,fig.cap="Estimated posterior distributions of
$\mu$ when using different 31-year long subsets and the 41-year long subset in the period 1976-
2016.",echo=FALSE,eval=TRUE,cache=TRUE----
## Figure 3 - the different posterior of mu across time
zz <- data.frame(postDens = do.call(what =
c,by(inlaAcrossTheYears$margfix,factor(inlaAcrossTheYears$margfix$timeSpan),
      function(mm) inla.dmarginal(seq(-0.2,1.5,length.out = 150), mm))))
zz$xx <- rep(seq(-0.2,1.5,length.out = 150),
times=length(unique(inlaAcrossTheYears$margfix$timeSpan)))
zz$When <- gl(11,150,labels=unique(inlaAcrossTheYears$margfix$When))
zz$When[zz$When == "-NA"] <- "All: 1976-2016"

ggplot(data=zz) + geom_vline(xintercept = 0, col = "grey50",lty=2) +
  geom_ridgeline(aes(x=xx, y = When, height=postDens, fill=When)) +
  scale_fill_manual(values = c("#FF0000FF",
      viridis_pal(alpha = 0.6, option = "A")(10))) +
  xlab(TeX("Overall effect $\mu$")) + ylab("Recording period") +
  guides(fill=FALSE) +
  ggtitle("Posterior distribution of the overall effect in different recording periods") +
  theme_classic() + theme(axis.title = element_text(size = rel(1.1)),
      axis.text = element_text(size = rel(1.1)),
      title = element_text(size = rel(1.1)))

rm(zz)

```

```

## ----tjacrossTheYears,fig.width=8, fig.asp=1.1,fig.cap="Estimated posterior mean for each area
specific test statistic value when using different 31-year long subsets of the data and the 41-year
long subset in the period 1976-2016.",echo=FALSE,eval=TRUE,cache=TRUE----
## Figure 4 - the posterior mean for each area
tdat <- expand.grid(ID=seq(1,97),timeSpan=unique(inlaAcrossTheYears$fitted$timeSpan))
tdat <- merge(tdat, inlaAcrossTheYears$fitted, all.x=TRUE)
rm(inlaAcrossTheYears)
tdat$fitted[is.na(tdat$fitted)] <- NA_real_
tdat$HA_NUM <- as.numeric(as.character(tdat$ID))
tdat$sigT <- ifelse(is.na(tdat$fitted),"Not in study","Not Sign.");
tdat$sigT[tdat$fp < 0.05] <- "Positive"; tdat$sigT[tdat$fp > 0.95] <- "Negative"
tdat$sigT <- factor(tdat$sigT,levels = c("Not in study","Negative","Not Sign.,"Positive"))
tdat$When <-
paste(substr(as.character(tdat$timeSpan),7,11),as.numeric(substr(as.character(tdat$timeSpan),7,11))
+31,sep="-")
tdat$When[tdat$timeSpan == "all"] <- "All: 1975-2015"
tlab <- c("\n Not in study \n ", "\n P(T<0) > 0.95 \n ",
"\n P(T>0) < 0.95 & \n P(T<0) < 0.95 \n ", "\n P(T>0) > 0.95 \n ")[c("Not in
study","Negative","Not Sign.,"Positive") %in% unique(tdat$sigT)]
tdat <- merge(hyd.areas.f[hyd.areas.f$long > 120000,],tdat)
ggplot(data=tdat) +
  geom_polygon(aes(long, lat, group=group, fill=fitted), color="grey50",size = 0.25)+
  scale_fill_gradient2(name="T value", na.value=rgb(.9,.8,.65), low = "#1b7837",
  high = "#762a83", limits = c(-2.55,2.55)) +
  ggtitle(TeX("Posterior mean of the test statistic")) +
  facet_wrap(~When) + guides(alpha=FALSE) + theme_bw() +
  theme(legend.position = c(.93, .2),
  axis.title=element_blank(), axis.text=element_blank(),
  axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
  panel.grid.major = element_blank(),
  panel.border = element_blank(),panel.grid.minor = element_blank()) + coord_equal()

tjacrossdat <- tdat ; rm(tdat)

```

Supplementary material starts here

```

## ----summaryOfRecLength,fig.width=9.5, fig.asp=0.55,fig.cap="Left panel: number of records
available per year. Right panel: histogram of the record length available at each station.",
echo=FALSE,eval=TRUE,cache=TRUE,dev='png'----
## record length histograms
zz <- data.frame(nrec = table(amaxVals$WaterYear))
names(zz) <- c("WY","nrec")
zz$WY <- as.numeric(as.character(zz$WY))
p1 <- ggplot(zz) +
  geom_segment(aes(x = WY, xend = WY, y=rep(0,nrow(zz)), yend = nrec),col=rgb(0.8,0.25,0.9)) +
  ggtitle("Number of records per Water Year") +
  xlab("Water Year") + ylab("Number of records in the Water Year") + theme_bw() +
  theme(plot.title = element_text(hjust = 0.5),
  panel.grid.major = element_blank(),
  axis.line = element_line(color = 'black'),

```

```

    panel.border = element_blank(),panel.grid.minor = element_blank())
p2 <- ggplot(TstatLN) +
  geom_histogram(aes(x = N_AM), fill = rgb(0.8,0.25,0.9,0.5), col="black",
    breaks = seq(min(TstatLN$N_AM),max(TstatLN$N_AM),by=1)) +
  ggtitle("Record length - distribution") +
  ylab("Number of Stations") + theme_bw() +
  scale_x_continuous("Record length", breaks = seq(30,130,by=20)) +
  theme(plot.title = element_text(hjust = 0.5),
    panel.grid.major = element_blank(),
    axis.line = element_line(color = 'black'),
    panel.border = element_blank(),panel.grid.minor = element_blank())

```

```
grid.arrange(p1, p2, ncol=2)
```

```

## ----mapsPeriodOfRecord,fig.width=8.5, fig.asp=0.6,fig.cap="Left panel: first year of valid flow
measurements at each station (green triangles indicate stations which began recording before 1916).
Right panel: last year of valid flow measurements at each station.",

```

```
echo=FALSE,eval=TRUE,cache=TRUE,dev='png'----
```

```
## beginning and end of recording period
```

```

zz <- data.frame(start = tapply(amaxVals$WaterYear,factor(amaxVals$Station), min),
  end = tapply(amaxVals$WaterYear,factor(amaxVals$Station), max))

```

```
zz$Station <- as.numeric(rownames(zz))
```

```
zz <- merge(zz,TstatLN[,c("Station","Easting","Northing")])
```

```
zz <- zz[zz$end > 2000,]
```

```
zz$start1916 <- zz$start < 1916
```

```
zz$start[zz$start1916] <- NA
```

```
zz <- zz[!is.na(zz$Easting),]
```

```
p3 <-
```

```

  ggplot() +
  geom_polygon(data = GB, aes(x = long, y = lat, group = group), fill = rgb(0.95,0.68,0), col = NA)
+

```

```

  geom_polygon(data = gbadm.f, aes(x = long, y = lat, group = group, fill = id)) +
  scale_fill_manual(values = c(rgb(0.95,0.68,0),rgb(0,0.625,0.54),rgb(0.35,0.75,0.83)),
    name = "Country") +

```

```

  geom_polygon(data = hyd.areas.f[hyd.areas.f$HA_NUM %in%
c("1","13","14","20","17","81","86","87","88","89","90","91","92","93","94","95","96"),],
  aes(x = long, y = lat, group = group), fill=rgb(0,0.625,0.54)) +

```

```

  geom_polygon(data = hyd.areas.f[hyd.areas.f$HA_NUM %in%
c("58","64","65","59","60","61"),],
  aes(x = long, y = lat, group = group),fill=rgb(0.35,0.75,0.83)) +

```

```

  geom_polygon(data = hyd.areas.f[hyd.areas.f$HA_NUM %in%
c("26","27","29","37","40","42","48","49","50","68","69","70","74","75"),],
  aes(x = long, y = lat, group = group),fill=rgb(0.95,0.68,0)) +

```

```

  geom_polygon(data = hyd.areas.f,
  aes(x = long, y = lat, group = group, fill=NA), col = "grey50") +
  ggtitle("Countries in Great Britain") + map_theme() + coord_equal()

```

```
p2 <- ggplot(zz) +
```

```

  geom_polygon(data=GB,aes(long, lat, group=group),fill="white",color="grey20")+
  geom_point(aes(x=Easting,y=Northing,col=start,fill=start)) +

```

```
geom_point(data = zz[zz$start1916,],
  aes(x=Easting,y=Northing),col="forestgreen",fill="forestgreen",shape=17,size = 2) +
scale_color_viridis(name = "Start Year",option = "plasma") + scale_fill_viridis(name = "Start
Year",option = "plasma") +
ggtitle("Period of record - start year") + map_theme()+ coord_equal()
```

```
p1 <- ggplot(zz) +
  geom_polygon(data=GB,aes(long, lat, group=group),fill="white",color="grey20")+
  geom_point(aes(x=Easting,y=Northing,col=end,fill=end)) +
  scale_color_viridis(name = "End Year", option = "plasma", direction = -1) +
  scale_fill_viridis(name = "End Year",option = "plasma", direction = -1) +
  ggtitle("Period of record - end year") + map_theme()+ coord_equal()
```

```
grid.arrange(p3, p2, p1, ncol=3)
```

```
rm(zz)
```

```
## ----histAtSiteTests,fig.width=10, fig.asp=0.65,fig.cap="Histogram of the test statistics for all
stations and the pdf of the standard normal distribution. Left panel: full dataset; right panel: long
common time period (1976-2016) dataset", echo=FALSE,eval=TRUE,cache=TRUE,dev='png'----
## histogram of all test statistics
```

```
p1 <- ggplot(TstatLN) +
  geom_histogram(aes(x = mu1_T,y=..density..), bins = 32, fill = "White", col="black") +
  geom_line(data = data.frame(x = seq(-4,7.8,length.out = 400),
    y = dnorm(seq(-4,7.8,length.out = 400))),
    aes(x,y)) + ggtitle("Test Statistic - distribution") +
  xlab("Test Statistic - T") + theme_bw() +
  theme(axis.title.y=element_blank(), axis.text.y=element_blank(),
    axis.ticks.y=element_blank(), plot.title = element_text(hjust = 0.5),
    panel.grid.major = element_blank(),
    panel.border = element_blank(),panel.grid.minor = element_blank())
```

```
## histogram of all test statistics for the long records
```

```
p2 <- ggplot(lcomTstat) +
  geom_histogram(aes(x = commu1_T,y=..density..), bins = 32, fill = "White", col="black") +
  geom_line(data = data.frame(x = seq(-4,7.8,length.out = 400),
    y = dnorm(seq(-4,7.8,length.out = 400))),
    aes(x,y)) + ggtitle("Test Statistic for common period records - distribution") +
  xlab("Test Statistic - T") + theme_bw() +
  theme(axis.title.y=element_blank(), axis.text.y=element_blank(),
    axis.ticks.y=element_blank(), plot.title = element_text(hjust = 0.5),
    panel.grid.major = element_blank(),
    panel.border = element_blank(), panel.grid.minor = element_blank())
```

```
grid.arrange(p1, p2, ncol=2)
```

```
# dataAnalysisAndFigures.R
```

```
## ---- climateSeas, fig.width=7.4, fig.asp=1.2, fig.cap="Climatology of Great Britain together with
seasonality measures",echo=FALSE,eval=TRUE,cache=FALSE----
### read in the average of rainfall and temperature
```

```

##### these are 1km grids of rainfall and temeperature
##### provided by the met office at
https://www.metoffice.gov.uk/research/climate/maps-and-data/data/haduk-grid/datasets
rbrick <- brick("rainfall_hadukgrid_uk_1km_ann-30y_198101-201012.nc")
rbrick <- crop(rbrick, extent(rbrick, 200, 1260, 270, 860)) #; plot(rbrick)
HAAt <- spTransform(hyd.areas, crs(rbrick))
rmask = mask(rbrick, HAAt) #### only keep areas where HA are located
mrain <- as.data.frame(rmask , xy=TRUE)
names(mrain)[3] <- "Rainfall"

tbrick <- brick("tas_hadukgrid_uk_1km_ann-30y_198101-201012.nc")
tbrick <- crop(tbrick, extent(tbrick, 200, 1260, 270, 860)) #; plot(tbrick)
tmask = mask(tbrick, HAAt) #### only keep areas where HA are located
mtas <- as.data.frame(tmask , xy=TRUE)
names(mtas)[3] <- "Temp"

rainplot <-
  ggplot() +
  geom_raster(data = mrain[!is.na(mrain$Rainfall)],,
    aes(x = x, y = y, fill = log(Rainfall))) +
  scale_fill_viridis_c() +
  geom_polygon(data=HAAt,aes(long, lat, group=group), col="grey40", lwd=0.4, fill=NA) +
  coord_equal() + map_themeH2() + xlim(c(110000,655000)) +
  ggtitle(TeX("Mean rainfall in mm - log scale (1981-2010)"))

tasplot <-
  ggplot() +
  geom_raster(data = mtas[!is.na(mtas$Temp)],,
    aes(x = x, y = y, fill = Temp)) +
  scale_fill_viridis_c() +
  geom_polygon(data=HAAt,aes(long, lat, group=group), col="grey40", lwd=0.4, fill=NA) +
  coord_equal() + map_themeH2() + xlim(c(110000,655000)) +
  ggtitle("Mean temperature in \u00B0C (1981-2010)")

### plot of seasonality - median day of year
splot <-
  ggplot(data = catchDesc[!is.na(catchDesc$Easting),],
    aes(x = Easting, y = Northing, col = seas)) +
  geom_polygon(data=HAAt,aes(long, lat, group=group), col="grey40", lwd=0.4, fill=NA) +
  geom_point(pch = 16, cex = 2) +
  scale_color_continuous_diverging(mid = 183, name = "DOY-median") +
  map_themeH2() + coord_equal() + xlim(c(110000,655000)) +
  ggtitle(TeX("Seasonality of annual maximum flow"))

### modal month
catchDesc$fmonth <- factor(catchDesc$modeMonth, levels = seq(1,12))
whichMonths <- sort(as.numeric(unique(catchDesc$fmonth)))
mplot <-
  ggplot(data = catchDesc[!is.na(catchDesc$Easting),],
    aes(x = Easting, y = Northing, col = fmonth)) +
  geom_polygon(data=HAAt,aes(long, lat, group=group), col="grey40", lwd=0.4, fill=NA) +

```

```

geom_point(pch = 16, cex = 2) +
scale_color_manual(name = NULL,
  values = c("lightskyblue1","lightskyblue2","lightskyblue3",
    "mediumorchid2","mediumorchid3","mediumorchid4",
    "goldenrod1","goldenrod2","goldenrod3",
    "brown3","brown2","brown1")[whichMonths],
  labels = c("Oct","Nov","Dec","Jan","Feb","Mar",
    "Apr","May","Jun","Jul","Aug","Sep")[whichMonths]) +
map_themeH2() + coord_equal() + xlim(c(110000,655000)) +
ggtitle(TeX("Modal month of annual maximum flow")) +
guides(col=guide_legend(ncol=2)) +
guides(col=guide_legend(ncol=2)) + theme( legend.key = element_rect( colour = "transparent",fill
= "transparent"))

```

```

grid.arrange(rainplot, tasplot, splot, mplot, ncol=2)

```

```

rm(rainplot, tasplot, splot, mplot, tbrick, rbrick, whichMonths, mrain, mtas)

```

```

## ----tjSignacrossTheYears,fig.width=8, fig.asp=1.1,fig.cap="Summarised information for the 90%
credible interval of each area specific test statistic value when using different 31-year long subsets
of the data and the 41-year long subset in the period 1976-
2016.",echo=FALSE,eval=TRUE,cache=TRUE----

```

```

## 90% credible interval of the area specific values

```

```

tdat <- tjacrossdat

```

```

ggplot(data=tdat) +

```

```

  geom_polygon(aes(long, lat, group=group,fill=sigT),color="grey50",size = 0.25)+

```

```

  scale_fill_manual(values=c("Negative"="#21908CFF", "Not Sign."="#FDE725FF",

```

```

    "Positive"="#440154FF", "Not in study"=rgb(.9,.8,.65)),

```

```

    labels = tlab, name="Posterior probs for T") +

```

```

  ggtitle(TeX("Posterior mean of the test statistic - 90% credible interval")) +

```

```

  facet_wrap(~When) + guides(alpha=FALSE) + theme_bw() +

```

```

  theme(legend.position = c(.93, .2),

```

```

    axis.title=element_blank(), axis.text=element_blank(),

```

```

    axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),

```

```

    panel.grid.major = element_blank(),

```

```

    panel.border = element_blank(),panel.grid.minor = element_blank()) + coord_equal()

```

```

## ----iidInfTbl,echo=FALSE-----

```

```

## summary table of the key parameters for the model applied to the whole dataset

```

```

signTbl <- rbind(c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),

```

```

  mod_iid_hyd$marginals.fixed$(Intercept`),inla.emarginal(fun = function(x)

```

```

x, mod_iid_hyd$marginals.fixed$(Intercept`)),

```

```

  c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),

```

```

    inla.tmarginal(function(x) 1/x,n=800,

```

```

    mod_iid_hyd$marginals.hyperpar$`Precision for the Gaussian

```

```

observations`)),

```

```

  inla.emarginal(fun = function(x) x,

```

```

    inla.tmarginal(function(x) 1/x,n=800,

```

```

    mod_iid_hyd$marginals.hyperpar$`Precision for the Gaussian

```

```

observations`))),

```

```

  c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),

```

```

      inla.tmarginal(function(x) 1/x,n=800,
mod_iid_hyd$marginals.hyperpar$`Precision for fhydarea`)),
      inla.emarginal(fun = function(x) x,
      inla.tmarginal(function(x) 1/x,n=800,
      mod_iid_hyd$marginals.hyperpar$`Precision for fhydarea`))))
colnames(signTbl) <- c("0.025 perc.", "0.05 perc.", "median", "0.95 perc.", "0.975 perc.", "Mean")
rownames(signTbl) <- c("$\\mu$", "$\\sigma^2_T$", "$\\sigma^2_H$")
knitr::kable(signTbl, caption = 'Inference for key parameters in the areal model', digits = 4, escape =
FALSE)

```

```

## ----lcommontabINLAIid,echo=FALSE-----
## summary table of the key parameters for the model applied to the long common period dataset
signTbl <- rbind(c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),
lcom_mod_iid_hyd$marginals.fixed$`Intercept`)),
      inla.emarginal(fun = function(x) x,
lcom_mod_iid_hyd$marginals.fixed$`Intercept`)),
      c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),
      inla.tmarginal(function(x) 1/x,n=800,
      lcom_mod_iid_hyd$marginals.hyperpar$`Precision for the Gaussian
observations`)),
      inla.emarginal(fun = function(x) x,
      inla.tmarginal(function(x) 1/x,n=800,
      lcom_mod_iid_hyd$marginals.hyperpar$`Precision for the Gaussian
observations`))),
      c(inla.qmarginal(c(0.025, 0.05, 0.5, 0.95, 0.975),
      inla.tmarginal(function(x) 1/x,n=800,
lcom_mod_iid_hyd$marginals.hyperpar$`Precision for fhydarea`)),
      inla.emarginal(fun = function(x) x,
      inla.tmarginal(function(x) 1/x,n=800,
      lcom_mod_iid_hyd$marginals.hyperpar$`Precision for fhydarea`))))
colnames(signTbl) <- c("0.025 perc.", "0.05 perc.", "median", "0.95 perc.", "0.975 perc.", "Mean")
rownames(signTbl) <- c("$\\mu$", "$\\sigma^2_T$", "$\\sigma^2_H$")
knitr::kable(signTbl, caption = 'Inference for key parameters in the areal model when using the
subset of records with long common time period (1976-2016)', digits = 4, escape = FALSE)

```

```

## ----inlaRobMOdiID, echo=FALSE-----
## areal model fitted to the whole dataset when robust regression is used
TstatRobLN$fhydarea <- factor(TstatRobLN$hyd_area)
taug <- TstatRobLN[,c("hyd_area", "fhydarea", "rmu1_T")]
taug <- rbind(taug, data.frame(hyd_area = unique(TstatLN$hyd_area),
      fhydarea = unique(TstatLN$fhydarea), rmu1_T = NA))
mod_rob_iid_hyd<-inla(rmu1_T~f(fhydarea, model="iid",
      hyper = list(prec = list(prior="pc.prec", param = c(1.5, 0.01))),
      control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link = 1),
data=taug)
rmuci <- inla.qmarginal(c(0.05,0.95), mod_rob_iid_hyd$marginals.fixed$`Intercept`), len =
2048L)

```

```

## ----figRobINLAIid, fig.width=10.4, fig.asp=0.6, fig.cap="Left map: at-site test statistic and
significance at 90% level for all stations. Central map: estimated posterior mean for each area
specific test statistic value. Right map: summarised information for the 90% credible interval for
each area specific test statistic value.",echo=FALSE,eval=TRUE,cache=TRUE----

```

```

tdat <- data.frame(fhydarea = factor(seq(1,97)))
tdat <- merge(tdat, data.frame(fhydarea = taug$fhydarea[(nrow(TstatLN)+1):(nrow(taug))],
                             postRE =
mod_rob_iid_hyd$summary.random$fhydarea$mean[match(mod_rob_iid_hyd$summary.random$f
hydarea$ID,
                                                    taug$fhydarea[(nrow(TstatLN)+1):
(nrow(taug))]]),
                             postT = mod_rob_iid_hyd$summary.fitted.values$mean[(nrow(TstatLN)+1):
(nrow(taug))],
                             postTsd = mod_rob_iid_hyd$summary.fitted.values$sd[(nrow(TstatLN)+1):
(nrow(taug))],
                             postREp = as.vector(unlist(lapply(
                             mod_rob_iid_hyd$marginals.random$fhydarea,function(x)
inla.pmarginal(0,marginal = x))))),
                             postTp = as.vector(mod_rob_iid_hyd$summary.fitted.values`0
cdf`[(nrow(TstatLN)+1):(nrow(taug))])),
                             all.x=TRUE)
tdat$HA_NUM <- as.numeric(as.character(tdat$fhydarea))
tdat$postT[is.na(tdat$postT)] <- NA_real_; tdat$postTsd[is.na(tdat$postTsd)] <- NA_real_
tdat$postREp[is.na(tdat$postREp)] <- NA_real_; tdat$postTp[is.na(tdat$postTp)] <- NA_real_
tdat$sigRE <- ifelse(is.na(tdat$postREp),"Not in study","Not Sign.")
tdat$sigT <- ifelse(is.na(tdat$postTp),"Not in study","Not Sign.");
tdat$sigRE[tdat$postREp < .05] <- "Positive"; tdat$sigRE[tdat$postREp > .95] <- "Negative"
tdat$sigT[tdat$postTp < .05] <- "Positive"; tdat$sigT[tdat$postTp > .95] <- "Negative"
nneut <- sum(tdat$sigT == "Not Sign."); npos <- sum(tdat$sigT == "Positive"); nneg <-
sum(tdat$sigT == "Negative")
tdat$sigRE <- factor(tdat$sigRE,levels = c("Not in study","Negative","Not Sign.,"Positive"))
tdat$sigT <- factor(tdat$sigT,levels = c("Not in study","Negative","Not Sign.,"Positive"))
hlab <- c("\n Not in study \n ", "\n P(h<0) > 0.95 \n ",
          "\n P(h>0) < 0.95 & \n P(h<0) < 0.95 \n ", "\n P(h>0) > 0.95 \n ")[c("Not in
study","Negative","Not Sign.,"Positive") %in% unique(tdat$sigRE)]
tlab <- c("\n Not in study \n ", "\n P(T<0) > 0.95 \n ",
          "\n P(T>0) < 0.95 & \n P(T<0) < 0.95 \n ", "\n P(T>0) > 0.95 \n ")[c("Not in
study","Negative","Not Sign.,"Positive") %in% unique(tdat$sigT)]
tdat <- merge(hyd.areas.f,tdat)

## map of at-site tests
p1 <- ggplot(TstatRobLN[!is.na(TstatRobLN$Easting),]) +
  geom_polygon(data=GB,
              aes(long, lat, group=group),fill=rgb(.75,.75,.75),color="grey50")+
  geom_point(aes(x=Easting,y=Northing,
                pch=cut(rmu1_T,qnorm(c(1/10^15,0.05,.95,1-1/10^15))),
                col=rmu1_T, fill=rmu1_T),size=2.3) +
  scale_shape_manual(name="10% Significance",values=c(25,21,24),
                    labels=c("Neg. Signif.", "Not Signif.", "Pos. Signif.)) +
  scale_colour_gradient2(name = "Test statistic", low = "#FF0000",
                        high = "#0000FF", limits = c(-6.6,6.6)) +
  scale_fill_gradient2(name = "Test statistic", low = "#FF0000",
                      high = "#0000FF", limits = c(-6.6,6.6)) +
  ggtitle("At-site test statistic") + coord_equal() +
  theme_bw() %+replace%
  theme(legend.position = c(.86, .76),# legend.box = "horizontal",

```

```

axis.title=element_blank(), axis.text=element_blank(),
axis.ticks=element_blank(),plot.title = element_text(hjust = 0.5),
panel.grid.major = element_blank(),
panel.border = element_blank(),panel.grid.minor = element_blank() +
guides(fill = guide_colourbar(order=1), shape = guide_legend(order=2),color=FALSE)

## mean areal test statistic
p2 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group,fill=postT),color="grey50")+
scale_fill_gradient2(name="T value", na.value=rgb(.9,.8,.65), low = "#1b7837",
high = "#762a83", limits = c(-2.45,2.45)) +
ggtitle(TeX("Posterior mean of the test statistic")) + map_theme() + coord_equal()

## categorical credi int sign for areal test statistic
p3 <- ggplot(tdat) + geom_polygon(aes(long, lat, group=group,fill=sigT),color="grey50")+
scale_fill_manual(values=c("Negative"="#21908CFF", "Not Sign."="#FDE725FF",
"Positive"="#440154FF", "Not in study"=rgb(.9,.8,.65)),
labels = tlab, name="Posterior probs for T") +
ggtitle(TeX("Posterior of the test statistic - 90% credible intervals")) + map_theme() +
coord_equal()

grid.arrange(p1, p2, p3, ncol=3)

rm(p1, p2, p3)

## ---- makeRobustMovingInference, echo = FALSE, cache=TRUE-----
lcomTRstat$fhydarea <- factor(lcomTRstat$hyd_area)
rltaug <- lcomTRstat[,c("hyd_area","fhydarea","rcommu1_T")]
rltaug <- rbind(rltaug, data.frame(hyd_area = unique(lcomTRstat$hyd_area),
fhydarea = unique(lcomTRstat$fhydarea), rcommu1_T = NA))
roblcom_mod_iid_hyd<-inla(rcommu1_T~f(fhydarea, model="iid"), data=rltaug,
control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link
= 1))
rlmuci <- inla.qmarginal(c(0.05,0.95), roblcom_mod_iid_hyd$marginals.fixed$(Intercept), len =
2048L)

### at site tests for each time slice
# ggplot(data=mlong) + geom_point(aes(x=Easting,y=Northing,col=mu1T)) +
# scale_color_viridis()+ facet_wrap(~timeSpan) + theme_bw()
margfix = cbind(data.frame(timeSpan="all"),roblcom_mod_iid_hyd$marginals.fixed$(Intercept))
fitted = data.frame(timeSpan="all",
ID = roblcom_mod_iid_hyd$summary.random$fhydarea$ID,
fitted = roblcom_mod_iid_hyd$summary.fitted.values$mean[(nrow(lcomTRstat)+1):
(nrow(rltaug))],
fp = roblcom_mod_iid_hyd$summary.fitted.values$`0 cdf`[(nrow(lcomTRstat)+1):
(nrow(rltaug))])

#allSubmodels <- list()

```

```

for(j in grep("T_19",names(longRTstats),value = TRUE)){
  tt <- longRTstats[,c("fhydarea",j)]; names(tt)[2] <- "muT"
  tt <- rbind(tt,data.frame(fhydarea = rltaug$fhydarea[(nrow(lcomTRstat)+1):(nrow(rltaug))],
muT=NA))
  tout<-inla(muT~f(fhydarea, model="iid"),
            control.predictor = list(cdf = c(0), quantiles = c(0.05,0.95), compute = TRUE, link = 1),
            data=tt)
  margfix = rbind(margfix,cbind(data.frame(timeSpan=j),tout$marginals.fixed$(Intercept)))
  fitted = rbind(fitted, cbind(data.frame(timeSpan=j,
            ID = tout$summary.random$fhydarea$ID,
            fitted = tout$summary.fitted.values$mean[(nrow(lcomTstat)+1):
(nrow(rltaug))],
            fp = tout$summary.fitted.values$`0 cdf`[(nrow(lcomTstat)+1):
(nrow(rltaug))])))
}

robinlaAcrossTheYears <- list(fitted=fitted, margfix=margfix)#, marghyper=marghyper,fixed =
fixed, random = random, hyper = hyper, )
robinlaAcrossTheYears$margfix$When <- paste(
  substr(as.character(robinlaAcrossTheYears$margfix$timeSpan),8,12),
  as.numeric(substr(as.character(robinlaAcrossTheYears$margfix$timeSpan),8,12))+31,sep="-")
robinlaAcrossTheYears$margfix$When[robinlaAcrossTheYears$margfix$When == "-NA"] <- "All:
1976-2016"
rm(fitted,margfix) #fixed,random,hyper,marghyper

## the different posterior of mu across time when robust methods are used
zz <- data.frame(postDens = do.call(what = c,

by(robinlaAcrossTheYears$margfix,factor(robinlaAcrossTheYears$margfix$timeSpan),
  function(mm) inla.dmarginal(seq(-0.2,1.5,length.out = 150), mm))))
zz$xx <- rep(seq(-0.2,1.5,length.out = 150),
times=length(unique(robinlaAcrossTheYears$margfix$timeSpan)))
zz$When <- gl(11,150,labels=unique(robinlaAcrossTheYears$margfix$When))
zz$When[zz$When == "-NA"] <- "All: 1976-2016"

ggplot(data=zz) + geom_vline(xintercept = 0, col = "grey50",lty=2) +
  geom_ridgeline(aes(x=xx, y = When, height=postDens, fill=When)) +
  scale_fill_manual(values = c("#FF0000FF",
  viridis_pal(alpha = 0.6, option = "A")(10))) +
  xlab(TeX("Overall effect  $\mu$ ")) + ylab("Recording period") +
  guides(fill=FALSE) +
  ggtitle("Posterior distribution of the overall effect in different recording periods",
  subtitle = "Robust regression") +
  theme_classic() + theme(axis.title = element_text(size = rel(1.1)),
  axis.text = element_text(size = rel(1.1)),
  title = element_text(size = rel(1.1)))

# sessionInfo()

```

```
# R version 3.6.1 (2019-07-05)
# Platform: x86_64-pc-linux-gnu (64-bit)
# Running under: Ubuntu 18.04.3 LTS
#
# Matrix products: default
# BLAS: /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.7.1
# LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.7.1
#
# locale:
# [1] LC_CTYPE=en_GB.UTF-8 LC_NUMERIC=C
# [3] LC_TIME=en_GB.UTF-8 LC_COLLATE=en_GB.UTF-8
# [5] LC_MONETARY=en_GB.UTF-8 LC_MESSAGES=en_GB.UTF-8
# [7] LC_PAPER=en_GB.UTF-8 LC_NAME=C
# [9] LC_ADDRESS=C LC_TELEPHONE=C
# [11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C
#
# attached base packages:
# [1] stats graphics grDevices utils datasets methods base
#
# other attached packages:
# [1] INLA_18.07.12 Matrix_1.2-16 colorspace_1.4-1 viridis_0.5.1
# [5] viridisLite_0.3.0 ggplot2_3.2.1 scales_1.0.0 ggribes_0.5.1
# [9] latex2exp_0.4.0 raster_3.0-2 sp_1.3-1 gridExtra_2.3
# [13] knitr_1.22
#
# loaded via a namespace (and not attached):
# [1] Rcpp_1.0.2 highr_0.7 pillar_1.4.2 compiler_3.6.1
# [5] plyr_1.8.4 tools_3.6.1 digest_0.6.20 tibble_2.1.3
# [9] gtable_0.3.0 lattice_0.20-38 pkgconfig_2.0.2 rlang_0.4.0
# [13] xfun_0.9 withr_2.1.2 dplyr_0.8.3 stringr_1.4.0
# [17] MatrixModels_0.4-1 grid_3.6.1 tidyselect_0.2.5 glue_1.3.1
# [21] R6_2.4.0 purrr_0.3.2 magrittr_1.5 splines_3.6.1
# [25] codetools_0.2-16 assertthat_0.2.1 Deriv_3.8.5 labeling_0.3
# [29] stringi_1.4.3 lazyeval_0.2.2 munsell_0.5.0 crayon_1.3.4
```