Evaluation of the performance of Euro-CORDEX regional climate models for assessing hydrological climate change impacts in Great Britain

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Evaluation of the performance of Euro-CORDEX Regional Climate Models for assessing hydrological climate change impacts in Great Britain: a comparison of different spatial resolutions and quantile mapping bias correction methods

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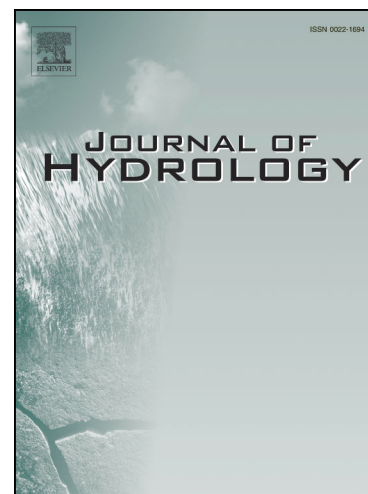
1 Title:

2 Evaluation of the performance of Euro-CORDEX Regional Climate Models for assessing hydrological
3 climate change impacts in Great Britain: a comparison of different spatial resolutions and quantile
4 mapping bias correction methods

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22   Regional Climate Models (RCMs) are an essential tool for analysing regional climate change impacts,

23 such as hydrological change, as they provide simulations with more small-scale details and expected

24 smaller errors than global climate models. There has been much effort to increase the spatial resolution

25 and simulation skill of RCMs (i.e. through bias correction), yet the extent to which this improves the

26 projection of hydrological change is unclear. Here, we evaluate the skill of five reanalysis-driven Euro-

27 CORDEX RCMs in simulating precipitation and temperature, and as drivers of a hydrological model to

28 simulate river flow on four UK catchments covering different physical, climatic and hydrological

29 characteristics. We use a comprehensive range of evaluation indices for aspects of the distribution such

30 as means and extremes, as well as for the structure of time series. We test whether high-resolution RCMs

31 provide added value, through analysis of two RCM resolutions, 0.44° (50 km) and 0.11° (12.5 km), which

32 are also bias-corrected employing the parametric quantile-mapping (QM) method, using the normal

33 distribution for temperature, and the Gamma (GQM) and Double Gamma (DGQM) distributions for

34 precipitation. The performance of these is considered for a range of meteorological variables and for the

35 skill in simulating hydrological impacts at the catchment scale.

36   In a small catchment with complex topography, the 0.11° RCMs clearly outperform their 0.44° version

37   for precipitation and temperature, but when used in combination with the hydrological model, fail to

38   capture the observed river flow distribution. In the other (larger) catchments, only one high-resolution

39   RCM consistently outperforms its low-resolution version, implying that in general there is no added value

40   from using the high-resolution RCMs in those catchments. Both resolutions produce river flow simulations

41   that cover the observed flow duration curve, but the ensemble spread is large and therefore the

42   simulations are difficult to use in practice. GQM decreases most of the simulation biases, except for

43   extreme precipitation and high flows, which are further decreased by DGQM, which also reduces the

44   multi-model simulation spread. Bias correction does not improve the representation of daily temporal

45   variability measured by the Nash-Sutcliffe Efficiency Index, but it does for monthly variability, in particular

46   when applying DGQM, which reduces most of the simulation biases. Overall, an increase in RCM resolution

47   does not imply a better simulation of hydrology and bias-correction represents an alternative to ease

48   decision-making.

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1.   Introduction

53   Global General Circulation Models (GCMs) are the main tool for climate change projections. However,

54   their spatial resolution is usually not finer than 100 km x 100 km (Rummukainen, 2016), limiting their skill

55   to simulate local climate. Regional Climate Models (RCMs) focus on specific subcontinental or subnational

56   domains, incorporating regional features such as topography, coasts and islands more accurately.

57   Consequently, RCMs improve the simulation of small-scale processes that affect precipitation, such as

58   orographic forcing (Rummukainen et al., 2015; Di Luca et.al, 2015), and are expected to yield more

59   accurate projections of climate change at finer spatial scales. RCMs have been used extensively to evaluate

60   the impacts of climate change on hydrology, such as changes in mean river flow, floods or low flows (e.g.

61   Kay et al., 2015; Kay and Jones, 2012; Mendoza et al., 2016; Teng et al., 2015; Prudhomme et al., 2013;

62   Cloke et al., 2013).

63   The resolution of RCMs has increased over time with the availability of higher computer power.

64   Currently, the spatial resolution of RCMs varies from 50 km x 50 km to less than 5 km x 5km (Rummukainen,

65 2016; Rockel et al., 2015). Due to their increased representation of regional features and small-scale

66 processes, RCMs generally simulate the current regional climate better than their driving data (Feser et al.

67 2011; Di Luca et al., 2015). Nevertheless, this might not be true in regions mainly influenced by large-scale

68 climatic processes (Eden et al., 2014). Therefore, the added value of high-resolution RCMs depends on

69 the analysed region, variable and context (Rummukainen, 2016).

70   An important driver for increasing RCM resolution is the need to improve the analysis of climate change

71 impacts for decision-making (e.g. Macadam et al., 2016; Qian et al., 2015). For hydrology, the standard

72 analysis of climate change impacts generally involves coupling uncorrected or bias-corrected GCM or RCM

73 precipitation and temperature outputs with hydrological models to simulate river flow scenarios (e.g.

74 Teutschbein and Seibert; 2012; Huang et al., 2014; Teng et al., 2015). In Great Britain, these studies focus

75 on one (or more) of four main topics: 1) the contribution of the GCMs, RCMs, emission scenarios and bias-

76 correction techniques to the uncertainty of the change projection (e.g. Prudhomme and Davies, 2009; Kay

77 et al., 2009; Arnell, 2011; Christierson et al., 2012), 2) the impact of the bias correction techniques on the

78 projections (e.g. Prudhomme et al., 2013; Cloke et al., 2013; Wetterhall et al., 2012; Kim et al., 2016), 3)

79 projections of future floods (Cloke et al., 2013; Kay et al., 2015; Wetterhall et al., 2012; Kay and Jones,

80 2012), and, 4) projections of future low flows (Wilby and Harris, 2006; Arnell, 2011; Fowler and Kilsby,

81 2007).

82   Some studies have identified a consistent improvement in hydrological simulation skill with increasing

83 RCM resolution for the annual mean river flow (Huang et al. 2014). For the simulation of river flow peaks

84 as a response to extreme precipitation events, previous studies found no improvement when increasing the

85 model resolution (Kay et al. 2015; Huang et al., 2014). Others studies found that the improvement depends

86 on the catchment size and on the evaluation index (Dankers et al. 2007), whilst others found an

87 improvement when simulating seasonal flow and hydrologic signatures aimed to represent diverse

88 hydrologic processes (e.g. runoff ratio, center time of runoff) (Mendoza et al., 2016). However, these studies

89 have only used one RCM to perform the comparison as, to date, there has been no systematic study using

90 a large number of RCM simulations to test the effect of RCM resolution on hydrological simulation skill.

91   The first aim of this paper is to use the EURO-CORDEX simulations (Jacob et al. 2014) to robustly

92   assess the added value of increasing RCM resolution on hydrological simulations. The Euro-CORDEX

93   simulations at 0.11° (12.5 km x 12.5 km) and 0.44° (50 km x 50km) have the same lateral boundaries and

94   the parameterisations of each RCM are the same at both resolutions, thus making them ideal for such a

95   comparison. This work builds on assessments of the 0.11° and 0.44° Euro-CORDEX RCMs at reproducing

96   observed temperature and precipitation distributions, including extremes and dry/wet spell lengths. Results

97   vary among the studies. Some found a higher accuracy for the 0.11 RCMs for Europe when evaluating the

98   mean and extreme precipitation at a daily and sub-daily temporal resolution (Prein et al. 2015, Fantini et al

99   2016), whereas others did not find an improvement in accuracy when assessing the spatio-temporal

100   patterns of the monthly and seasonal precipitation and temperature (Kotlarski et al. 2014). For the Alps

101   Torma et al. (2015) found a higher skill for the 0.11 RCMs when simulating the spatial distribution of the

102   mean, extreme and intensity of precipitation, while Casanueva et al. (2016) showed for the Alps and Spain

103   that the best performance depends on the RCM, season and validation index when evaluating precipitation

104   intensity, frequency, mean and extremes.

105   Biases in RCM simulations are due to parameterisation of sub-grid processes, limited representation

106   of local features, incorrect boundary conditions and differences between spatial resolutions of the

107   simulations and observations (Ehret et al., 2012; Benestad, 2010). Therefore, RCMs require post-

108   processing for many applications (Christensen et al., 2008). Statistical bias-correction techniques reduce

109   biases in the mean, variance or the complete distribution of simulated climate variables (reviews in Maraun

110   et al., 2010; Teutschbein and Seibert, 2012; Maraun and Widmann, 2018; Lafon et al., 2013). Quantile

111   mapping (QM) is one of the standard techniques used (Piani et al., 2010; Teutschbein and Seibert, 2012;

112   Maurer et al., 2014). Whilst effective, bias correction has important limitations that are further discussed in

113   the conclusions.

114   To date, a detailed comparison of the simulation skill of bias-corrected high- and low-resolution model

115   outputs for aspects that are important for hydrological studies (e.g. means, extremes, daily sequence) has

116   not been undertaken. The second aim of this study addresses this research gap by conducting a detailed

117   evaluation of aspects that are relevant for the hydrological regime such as seasonal precipitation,

118 occurrence of extreme events, and monthly and daily pairwise indices (assess the skill to reproduce the

119 observed time-series). The evaluation of these aspects allows identifying the capabilities and weaknesses

120 of the impact assessments. Here, the simulations are evaluated against gauged data, working as a mean

121 to assess the plausibility of the simulation outputs using uncorrected and bias-corrected RCMs. This work

122 builds on studies that have assessed climate variables. For instance, the bias-corrected Euro-CORDEX

123 simulations, at both resolutions, have a similar skill at capturing the wet-day intensity and precipitation

124 frequency (Casanueva et al., 2016).

125 Here, we therefore address the two above-mentioned research aims by evaluating the simulation skill

126 of five uncorrected and bias-corrected Euro-CORDEX RCMs at 0.11° and 0.44° using a range of

127 temperature, precipitation and river flow indices, evaluating the mean along with high and low extremes,

128 frequency of occurrence and daily and monthly simulation sequence. By using a multi-model ensemble,

129 this analysis provides a robust understanding of the added value of high-resolution simulations and post-

130 processing approaches for hydrological impact studies. We analyse four diverse catchments across Great

131 Britain, representative of different climate and physical characteristics, focusing on the following questions:

132 1)   Based on a range of selected indices, is the performance of the 0.11° Euro-CORDEX RCMs better

133   than their 0.44° version to simulate (a) climate and (b) river flow?

134 2)   Is the current skill of the Euro-CORDEX RCMs sufficient to generate plausible inputs for the

135   analysis of climate change impacts on hydrology and how does this compare to the inputs from

136   bias-corrected simulations?

137 3)   Is there any improvement in the simulation skill of precipitation and river flow when using a Double

138   Gamma Quantile Mapping (DGQM) bias correction compared to the usual Gamma Quantile

139   Mapping (GQM) approach?

140 Given the associated computational cost (Bucchignani et al., 2016) and the potential for improving the

141 skill of climate simulations, especially for impact assessments (Ehret et al., 2012), there is a clear need for

142 rigorous evaluation of the added value of increasing RCM resolution. Previous hydrological impact studies

143 have analysed this issue using one or two RCMs (e.g. Mendoza et al., 2016; Kay et al., 2015). However,

144 their results might not be transferable to other RCMs, as each has its own parameterisations.

145   GQM inflates the precipitation extremes, producing unreliable flood simulations. Whilst this is a known

146   issue (Cloke et al., 2013; Huang et al., 2014), no study has exhaustively compared the results between

147   using the GQM and the DGQM approaches using extreme indices. This study provides a comprehensive

148   analysis of such gaps.

149   **2.   Data and method**

150   **2.1. Observation databases and study catchments**

151   The observations are used to calibrate the hydrological model (Section 2.2), develop the bias

152   correction method (Section 2.3) and to compare the outputs of the RCMs to evaluate their simulation skill

153   (Section 2.5). We employ gridded observations based on weather stations, as these are better comparable

154   to the outputs of the climate models which produce an areal average for each gridbox (following Osborn

155   and Hulme, 1997). We use the Centre for Ecology and Hydrology (CEH) Gridded Estimates of Areal Rainfall

156   (CEH-GEAR) dataset (Tanguy et al. 2014) as 1km x 1km gridded daily precipitation observations (Keller et

157   al., 2015). Records from the Natural Environment Research Council (NERC) Hydrology and Ecology

158   Research Support System (CHESS) (Robinson et al., 2017a, 2017b) are used as 1 km x 1 km gridded daily

159   temperature observations. The 1 km x 1 km gridded CHESS-PET dataset is employed as potential

160   evapotranspiration (PET) observational reference. CHESS-PET uses the Penman-Monteith equation

161   (Monteith, 1965) to calculate daily PET using climate variables from the Met Office Rainfall and Evaporation

162   Calculation System (MORECS) (Hough and Jones, 1997) as input. All these datasets cover the period 1961

163   to 2010. A detailed description of the methodology and weather stations used to develop the gridded

164   datasets can be found in Robinson et al. (2017a, 2017b) and Tanguy et al. (2014). We use river flow

165   observations from the CEH's National River Flow Archive (NRFA). The available river flow observations for

166   the 1961-2010 period varies in each catchment, with a minimum of 30 years of continuous records.

167   We analyse four catchments within the UK. The catchments have long river flow records and cover

168   regions that are representative of the different climate and catchment types that can be found within the

169   UK. These are the Upper Thames, Glaslyn, Calder and Coquet catchments (Fig. 1). This set of catchments

170   with different characteristics (Table 1) can aid identifying key features that impact on the simulation skill of

171   the RCMs. The smallest catchment is the Glaslyn, which has the most complex topography and highest

172   rainfall. The largest catchment is the Upper Thames (1616 km^2), which also has the least complex

173   topography. The Calder and Coquet are intermediate in terms of area, elevation and precipitation. These

174   catchments have been studied before using bias-corrected climate projections (QM, normal distribution for

175   temperature and Gamma distribution for precipitation) from the HadRM3-PPE RCM (Prudhomme et al.,

176   2013).

177   **2.2. RCMs**

178   We evaluate two spatial resolutions (0.11° equivalent to 12.5 km x 12.5 km and 0.44° equivalent to

179   50 km x 50 km) of five Euro-CORDEX RCMs (Jacob et al., 2014) driven by the ERA-Interim reanalysis (Dee

180   et al., 2011), the so-called 'evaluation simulations'. The evaluation simulations are used as these are driven

181   by observations and consequently simulate the internal variability in synchronicity with reality, in contrast

182   to the historical simulations. The assessed RCMs are shown in Table 2 (refer to Table 1 in Kotlarski et al.

183   (2014) and Table 1 in Prein et al. (2015) for a detailed RCM description). These models are selected as

184   they have the best performance to reproduce observations in the British Isles according to Kotlarski et al.

185   (2014). When more than one RCM cell is needed to fully cover the catchment we use the mean of the cells

186   to represent the catchment's climate simulations (see Fig. 1).

187   **2.3. Bias correction**

188   QM is used based on parametric representations of the simulated and observed distributions (Piani

189   et al., 2010). For each month of the year, the Gamma distribution is fitted to the observed and simulated

190   gridded daily precipitation and the normal distribution to the observed and simulated gridded daily

191   temperature. RCMs generally simulate too many days with very low precipitation and not enough dry days.

192   Therefore, in an initial step the QM method adjusts the number of simulated dry days in the RCM evaluation

193   simulations such that they match with the number of observed dry days by including a wet day threshold

194   and replacing all values below it with zero. After the wet-day adjustment, the distributions of the simulations

195   and observations are matched using their cumulative distribution functions (CDF). The method is

196   represented by the following equations:

197    $P_c(t) = F_g^{-1}(F_g(P_R(t), \alpha_R, \beta_R), \alpha_O, \beta_O)$ (1)

198 $$T_c(t) = F_n^{-1}\big(F_n\big(T_R(t),\mu_R,\sigma_R^2\big),\mu_O,\sigma_O^2\big) \qquad\qquad\qquad (2)$$

199

200   Where $P_c(t)$ and $P_R(t)$ represent the bias-corrected and raw RCM daily precipitation, respectively.

201 Likewise, $T_c(t)$ and $T_R(t)$ stand for the bias-corrected and raw RCM daily temperature. The raw RCM CDF

202 is symbolized with F, and F^{-1} stands for the observations inverse CDF. The 'g' and 'n' subscripts represent

203 the Gamma and normal distributions, respectively. The precipitation shape and scale parameters are

204 symbolised by α and β and the temperature mean and standard deviation by μ and σ, respectively. Finally,

205 the 'R' and 'O' subscripts are used to symbolize the distribution parameters from the raw RCM and

206 observations, respectively.

207   GQM focuses on the most frequent values (e.g. means) (Teng et al., 2015; Yang et al., 2010).

208 Consequently, the corrected precipitation extremes tend to be inflated compared to the observations

209 (Cannon et al., 2015). Therefore, we also bias-correct precipitation using the DGQM. The methodology is

210 mainly the same as the GQM with the difference that the simulated precipitation distribution is divided in

211 two segments. Each is corrected separately, generating correction parameters for each section. In our

212 study, the distribution is divided at the 90th percentile because at this percentile the biases inflate (see

213 section 3.2.2.1).

214   For the 0.11° RCMs, the spatial scale of the simulations and the observations are approximately the

215 same and the method can be viewed as a pure bias correction. In contrast, the output of the 0.44° is given

216 on a larger scale than the observations and thus the QM also includes a downscaling aspect to account for

217 the difference in distributions on different spatial scales. We note that due to the existence of sub-grid

218 variability QM is in principle problematic as the corrected values for all sub-grid locations would have

219 unrealistic high correlations (Maraun, 2013). However, this limitation is not of high relevance for our study

220 as we bias-correct the distributions for the entire catchments.

221   **2.4. Hydrological simulation**

222   The Hydrological Modeling System from the US Army Hydrologic Engineering Center (HEC-HMS)

223 (Scharffenberg, 2013) is used to simulate the catchments' daily river flow. HEC-HMS has been successfully

224 used before to analyse climate change impacts on water resources in other regions (e.g. Babel et al., 2014;

225   Azmat et al., 2015). An advantage of the model is the available guidance for the estimation of parameters.

226   Here, the model is run using its continuous, lumped arrangement. Observed precipitation and PET time

227   series are used as input for the calibration and validation of the model. Afterwards, the raw and bias-

228   corrected RCM simulations drive the model to generate the river flow simulations.

229   Evapotranspiration controls the moisture returning from the Earth's surface to the atmosphere and

230   therefore impacts on the river flow. PET estimates the amount of water returning to the atmosphere when

231   enough water is present in the surface of the catchment. Climate models do not simulate PET directly, thus

232   it is estimated indirectly with formulas using variables from the climate models as input. There is no

233   consensus on whether temperature–based or physically-based formulas provide better results in a climate

234   change context (Kay et al., 2013) as the data required by the physically-based formulas is uncertain in the

235   climate model simulations compared to the input from one variable formulas (Kingston et al., 2009). This

236   has been discussed and explored elsewhere (please refer to: Seiller and Anctil, 2016; Kingston et al., 2009;

237   Kay and Davies, 2008; Kay et al., 2013). We estimate PET using the Oudin formula (Oudin et al., 2005) as

238   it has given accurate results before (e.g. Oudin et al., 2005; Kay and Davies, 2008).

239

$$\begin{cases} PET \ (mm \ day^{-1}) = \frac{R_e}{\lambda \rho}\left(\frac{T+5}{100}\right) & if \ T+5 > 0 \\ PET \ (mm \ day^{-1}) = 0 & otherwise \end{cases} \tag{5}$$

240   The extraterrestrial solar radiation (R_e) is the solar radiation received at the top of the Earth's

241   atmosphere which can be estimated by the latitude and day of the year. The density of water is symbolized

242   by ρ, the latent heat flux by λ (2.45 MJ/kg) (Allen et al., 1998) and T is the daily mean temperature (°C).

243   When driven by observed temperature, the Oudin formula gave results similar to the CHESS-PET dataset

244   for 1973 to 2010 (Pasten-Zapata, 2017).

2.5. Hydrological model calibration

246   The hydrological model is calibrated and validated against the observations using a split sample

247   test. Considering the available uninterrupted daily river flow records, for each catchment two same-length

248   non-overlapping time periods are used: one for calibration and the other for validation. The period with

249   available river flow observations varies for each catchment. The period with observations for each

250   catchment is selected and divided into two equal-length, non-overlapping periods. Calibration is done for

251 the more recent period and validation for the other portion of the sample. Three indices are assessed: the

252 low flows simulation is evaluated using the Q95 (flow equalled or exceeded 95% of the time), the high flows

253 by the Q10 (flow equalled or exceeded 10% of the time) and the Nash-Sutcliffe Efficiency Index (NSE)

254 which evaluates the fit of the simulated and observed river flow. The NSE ranges from 1 (perfect fit) to

255 negative (unreliable model) (Nash and Sutcliffe, 1970). In the NSE formula, Q_t^{obs} and Q_t^{sim} stand for the

256 observed and simulated river flow at time step t, respectively. Q^{mean} is the average of the observed river

257 flows during the complete period.

258 $$NSE = 1 - \left[\frac{\sum_{t=1}^{n}(Q_t^{obs} - Q_t^{sim})^2}{\sum_{t=1}^{n}(Q_t^{obs} - Q^{mean})^2} \right] \qquad (6)$$

259 **2.6. RCM validation approach and indices**

260 Validation is important to assess the RCM simulation skill before and after bias correction (Eden et

261 al., 2014). Here, a five-fold cross-validation approach is used: 1) the study period is divided into five same-

262 length, non-overlapping blocks, and 2) the QM methods are trained using four blocks and the remaining

263 block is corrected using the parameters from the training period (Maraun et al., 2015). The corrected blocks

264 are concatenated to time series for the entire period from which the performance measures for the bias-

265 corrected precipitation and temperature are derived.

266 A range of distribution-based and time series-based indices evaluate the skill of the raw and bias-

267 corrected RCM outputs to simulate the observerd precipitation, temperature and river flow. The indices

268 assess biases in the means, low and high extremes, inter- and intra-annual variability and correlations for

269 each variable (see Table 3). RCMs are then ranked based on their skill to simulate all indices relative to the

270 skill of the other RCMs at both resolutions. As we are evaluating the outputs of 10 RCMs (5 high-resolution

271 and 5 low-resolution), each RCM is given a value between 1 (best) and 10 (worst) based on their simulation

272 skill. Thus, simulation skill refers to the biases present in the models compared to the available

273 observations considering all the metrics used in this study. We use the complete time series (dry days

274 included) to estimate the precipitation indices. Even when driven by "perfect boundary conditions", a close

275 similarity between the RCM simulations and observations is not expected (Kay et al., 2015) due to subgrid

276 variability or internal variability because the boundary conditions do not fully determine the weather states

10

277 within the RCM. Nevertheless, we include daily and monthly pairwise indices as these are important for the

278 river flow simulation. We left out the hydrological model uncertainty source intentionally to solely evaluate

279 the effects of increasing RCM resolution. Thus, we compare the river flow simulations driven by RCM

280 outputs against the river flow simulations driven by the observed temperature and precipitation.

281 **3. Results**

282   This section begins by showing hydrological model simulation skill followed by the evaluation of the

283 simulation skill of the uncorrected RCMs for temperature, precipitation and river flow. Finally, we compare

284 the biases that remain after bias-correcting precipitation using the GQM and DGQM and their impacts on

285 the river flow simulation.

286   **3.1. Calibration and validation of the hydrological model**

287   Firstly we evaluate the hydrological model simulation skill using climate observations as input.

288 Depending on the catchment, the length of the overall evaluation period ranges from 34 to 49 years. The

289 daily NSE varies between 0.62 (Calder) and 0.78 (Glaslyn) for calibration and between 0.52 (Coquet) to

290 0.78 (Glaslyn) for validation (Table 4). These results indicate a moderate to good simulation skill overall

291 compared to the NSE values from similar studies which vary from 0.45 to 0.9 (e.g. Arnell, 2011; Walsh et

292 al., 2015; Cloke et al., 2013). The Q10 bias ranges between -6% and 11% for the calibration and between

293 –5% and 7% for the validation. Similarly, the Q95 bias ranges between -27% and -11% for the calibration

294 and between -44% and 6% for the validation. Overall, the simulation of high flows is very good and moderate

295 to very good for the low flows. More detail on the calibration and validation results can be found in the work

296 from Pasten-Zapata (2017).

297   **3.2. Evaluation of the RCM simulation skill**

298   We now assess the skill of the RCMs at simulating climate and river flow, firstly for the raw

299 simulations and then for the bias-corrected outputs. We only show robust results for the analysis of the

300 indices (e.g. if all RCMs from a particular resolution underestimate or overestimate an index). We also

301 evaluate the multi-model percentile bias for each variable and use a skill rank to enable comparison of the

302 different RCMs over the different performance indices. The ranking is only estimated for the uncorrected

303 simulations as the biases after the correction are small and similar among the RCMs. Thus, ranking the

304 bias-corrected simulations would give meaningless results.

305 ### 3.2.1. Uncorrected RCM simulations

306 #### 3.2.1.1.   Temperature

307 We begin with assessing the ability of the RCMs to simulate temperature. The 0.11° RCMs

308 underestimate the annual mean temperature for the upper Thames (Fig. 2a, ii), Calder (Fig. 2c, ii) and the

309 Coquet (Fig. 2d, ii) catchments, whereas the 0.44° RCMs overestimate the annual mean temperature for

310 the Glaslyn (Fig. 2b, ii) and Coquet (Fig. 2d, ii) catchments. The monthly mean temperature bias for the

311 0.11° RCMs is larger for the Calder (between and 0.5 °C and 1.1 °C) (Fig. 2c, ii) and smaller for the Glaslyn

312 catchment (between 0.4 °C and 0.7 °C) (Fig. 2b, ii). In contrast, the monthly mean temperature bias of the

313 0.44° RCMs is larger for the Glaslyn (between 0.4 °C and 1.2 °C) (Fig. 2b, ii) and smaller for the Calder

314 catchment (between 0.8 °C and 1.0 °C) (Fig. 2c, ii).

315 We use the simulation spread to evaluate the simulation skill of each resolution. The spread

316 represents the range between the highest and lowest simulated value considering all RCMs at each

317 resolution and all gridcells within a catchment. The temperature percentile bias spread for the upper

318 Thames is similar for both resolutions except between the 40th and 60th percentile where the 0.44°

319 simulation include larger positive biases (Fig. 3a). For the Glaslyn catchment, the 0.44° simulations

320 overestimate temperature for almost all percentiles, while the biases of the 0.11° simulations are smaller

321 (Fig. 3b). For the Calder catchment, the 0.44° RCM spread includes the no bias threshold for all percentiles,

322 whereas the 0.11° RCMs underestimate temperature between the 40th and 90th percentile (Fig. 3c). Finally,

323 in the Coquet catchment the 0.44° simulations overestimate temperature below the 70th percentile and the

324 0.11° simulations underestimate it between the 40th and 80th percentiles (Fig. 3d). The Pearson correlation

325 coefficients of the daily time series vary between 0.91 and 0.97 in all catchments for both resolutions (Figs.

326 2, iii).

327 Integrating the RCM simulation skill of all the indices into a ranking shows that, in the upper Thames,

328 two out of five high-resolution uncorrected simulations outperform their 0.44° version (last column of Table

329 5). Similarly, for the Calder catchment, one 0.11° simulation outperforms its 0.44° version and all five high-

330 resolution simulations outperform their low-resolution version for the Glaslyn and Coquet catchments. This

331 indicates that topography has an influence in the simulation of temperature and RCM resolution has an

332 effect in the simulation skill for catchments with larger elevation variability where, for observations at high

333 elevation, the 0.44° RCMs would be expected to have positive biases as the grid elevation is lower that the

334 observations.

335 Based on the rank, the overall best performing simulation for the upper Thames and Calder

336 catchments is 0.44° RACMO, whereas for the Glaslyn and Coquet catchments, the 0.11° RACMO and

337 HIRHAM simulations, respectively, outperform the rest. This implies that biases from the high-resolution

338 simulations are smaller for the catchments with complex topography, which is better represented by the

339 0.11° simulations. The biases are a consequence of systematic model biases in the elevation and a lack of

340 representation of the elevation variability. Nevertheless, for larger and flatter catchments the simulation skill

341 from both resolutions is similar.

342 ### 3.2.1.2. Precipitation

343 Now we assess the skill of the uncorrected RCMs to simulate precipitation. Overall, RCMs have

344 biases when simulating extremes. For instance, the SDII ratio is underestimated in all catchments by the

345 0.44° simulations (Figs. 4a, S1a and S2a), except for the Coquet (Fig. S3a). In all catchments the RX1day

346 is overestimated by both resolutions between 24% and 93%. The R10 and R20 are underestimated at the

347 Glaslyn catchment between -23 and -77 days and between -16 and -45 days, respectively (Fig. S1d).

348 Similarly, in the Calder catchment R10 and R20 are underestimated by the 0.44° simulations between -5

349 and -10 days and between -3 and -4 days, respectively (Fig. S2d). These results indicate that the

350 uncorrected models can provide unrealistic simulations of extreme precipitation.

351 It is expected that the models simulate the precipitation mean better than the extremes. Even

352 though the spread of the models includes the observed mean precipitation for most catchments, there are

353 cases when this does not happen. The annual mean precipitation is underestimated by both resolutions in

354 the Glaslyn catchment between -22% and -67% (Fig. S1c). This may be because the analysed RCMs do

355 not correctly simulate convective precipitation. In the Calder catchment the 0.44° simulations underestimate

356 the annual mean precipitation between -7% and -16% (Fig. S2c). This can be due to local precipitation not

357 being correctly simulated by the coarse models. The absolute monthly mean precipitation bias for both

358 resolutions varies between 7% and 67% in all study cases (Figs. 4c, S1c, S2c and S3c).

359 The simulated precipitation bias spread increases in all catchments as the percentile increases.

360 The spread of the 0.11° simulations is larger than for the 0.44° simulations (Fig. 5, first row). In the upper

361 Thames catchment, the 0.11° simulations reach their largest spread, -1 to 4 mm/day, above the 95th

362 percentile whereas the largest spread of the 0.44° RCMs ranges from -1 to 1 mm/day (Fig. 5a). In the

363 Glaslyn catchment, the bias spread deviates from the observations at the 50th percentile for the 0.44°

364 simulations and at the 60th percentile for the 0.11° simulations (Fig. 5d). In the Calder catchment, the 0.11°

365 simulations spread includes the no bias threshold for the whole distribution whereas the 0.44° simulations

366 spread deviates from that threshold at the 70th percentile (Fig. 5g). In the Coquet catchment, the spread

367 from both resolutions includes the zero bias threshold for almost all percentiles (Fig. 5j).

368 The dry and wet spell biases are important for the simulation of river flow as this is influenced by

369 the daily sequence of the wet/dry conditions. The absolute dry spell bias for both resolutions in all

370 catchments range between 0.2 to 1.6 days, with a similar simulation skill in all catchments (Figs. 4b, S1b,

371 S2b, S3b). Likewise, the absolute wet spell bias for both resolutions varies between 0.1 and 1.6 days in all

372 catchments (Figs. 4b, S1b, S2b, S3b). Biases in the upper Thames for this measure are smaller, 0.2 to 0.6

373 days (Fig. 4b), compared to the other catchments. These results do not show large simulation biases.

374 Considering the time-series based indices, correlation coefficients are above 0.4 and below 0.8 in all

375 catchments, showing differences between the daily observations and simulations (Figs. 4c, S1c, S2c, S3c).

376 Considering the ranking for all indices, only for the Glaslyn catchment do all the 0.11° simulations

377 outperform their 0.44° version (Table 6, last column). From the five RCMs, two 0.11° simulations outperform

378 their low-resolution version for the Upper Thames and three for the Calder and Coquet catchments. The

379 0.11° CCLM and WRF have better simulation skill than their 0.44° version in all catchments. In contrast, for

380 HIRHAM and RCA, the improvement is only observed in one catchment. For the latter models, there is no

381 added value from increasing the resolution as the simulation processes occurring at higher resolutions than

382 the 0.44° gridbox do not improve the results, possibly due to an inappropriate physical representation. The

383   0.11° CCLM is the best performer in all catchments, except for the Glaslyn where 0.11° HIRHAM has the

384   highest rank.

385   All high-resolution simulations outperform their coarse simulations at the Glaslyn catchment due to

386   the differences between the sizes of the catchment and the different cells. Thus, increasing the RCM

387   resolution increases their simulation skill for catchments with larger elevation variability because the RCMs

388   are able to represent the high-resolution features. In general, increasing the RCM resolution reduces the

389   simulation biases in the upper tail of the distribution, but there are also high-resolution models that

390   consistently overestimate precipitation (e.g. RCA in Figs. 4, S1, S2, S3). The low-resolution models do not

391   simulate the small-sized catchment accurately. In contrast, the flat and large catchments are simulated

392   similarly by both resolutions, showing no added value from increasing RCM resolution.

393   ### 3.2.1.3.   River flow

394   Now, we evaluate the RCM skill in providing inputs for simulating the river flow in each catchment.

395   In the upper Thames, the 0.11° RCMs overestimate the spring discharge by between 16% and 194% (Fig.

396   6a). Both resolutions underestimate all indices in the Glaslyn catchment (Fig, S4). In the Calder catchment,

397   the 0.44° RCMs underestimate the annual (-9% to -31%) and autumn (-10% to -50%) flows, whereas the

398   0.11° RCMs overestimate the discharge during winter (3% to 63%) and spring (22% to 104%) (Fig. S5a).

399   Also, the Q10 and Q10 annual frequency are underestimated by the 0.44° RCMs (Fig. S5b and c). In the

400   Coquet catchment, the winter mean discharge is underestimated by the 0.44° RCMs by between -7% and

401   -42% and during summer it is overestimated by the 0.11° RCMs by between 2% and 218% (Fig. S6a). In

402   addition, the Q95 is overestimated by the 0.11° simulations.

403   Except for the Glaslyn catchment, the multi-model simulation spread of the flow duration curve

404   (FDC) from both resolutions includes the observed FDC entirely (Fig. 7, first row). For the Glaslyn catchment,

405   both resolutions underestimate the FDC with the 0.11° simulation spread being closer to the observed FDC

406   (Fig. 7d). The 0.44° simulation spread is larger than the 0.11° spread in the Coquet, but smaller in the upper

407   Thames. In the remaining catchments, the spreads of both resolutions are similar.

408   Overall, the maximum monthly NSE values are 0.42 for the Upper Thames (Fig. 6e), 0.22 for the

409   Glaslyn (Fig. S4e), 0.67 for the Calder (Fig. S5e) 0.26 for the Coquet catchment (Fig. S6e), indicating that

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410 the best river flow simulation is moderate to poor for all catchments except for the Calder. In contrast, the

411 minimum NSE values are negative in all catchments, implying that there are RCM outputs that generate

412 unreliable river flow simulations even at the monthly times step. Negative NSE values can be a result of

413 river flow overestimation in all indices, for instance 0.11° RCA and HIRHAM in the Calder and Coquet

414 catchments. The Spearman correlation coefficients of the daily river flow are higher for the upper Thames

415 and Calder and smaller for the Glaslyn and Coquet, indicating that the RCMs are able to simulate the daily

416 river flow sequence better on the large and flat sites compared to the small and topographically-complex

417 catchments (Fig. 67f, S4f, S5f and S6f).

418 Comparing their skill in simulating all indices by means of their rank, three 0.11° simulations

419 outperform their 0.44° version in the Upper Thames, five in the Glaslyn, one in the Calder and two in the

420 Coquet catchment (Table 7, last column). Overall, for both resolutions, biases in particular indices are large

421 and the skill of the pairwise indices (NSE, MSE, correlation) is low. The 0.11° simulation biases are

422 consistently smaller than the 0.44° biases only for the Glaslyn catchment due to the difference between the

423 catchment and the 0.44° RCM cell size. However, for this catchment biases are large even for the high-

424 resolution simulations indicating that subgrid processes that result in precipitation increases are not

425 represented by the models. Only CCLM gives better simulation skill for its high-resolution in all catchments.

426 ### 3.2.2. Bias-corrected RCM simulations

427 #### 3.2.2.1. Temperature

428 Bias-correction reduces the mean and percentile biases by construction (Figs. 3e,f,g,h). Thus, the

429 skill of all RCMs becomes similar in all catchments, as expected. Overall, the larger distribution biases are

430 for the 1st and 99th temperature percentiles, with biases lower than 1°C (Figs. 2, i). Even though these

431 percentiles have the largest biases after bias correction, as may be expected the biases are smaller than

432 those of the uncorrected RCMs. QM does not improve the daily sequence simulation. As a consequence,

433 there is only a slight change in the Pearson correlation coefficient of the daily time series (Figs. 2, iii).

434   **3.2.2.2.   Precipitation**

435   **3.2.2.2.1.   Gamma distribution QM**

436   The skill of both RCM resolutions becomes similar after application of GQM. Nevertheless, biases

437   are not reduced for the 95th percentile, SDII ratio, wet spell length, R95p and R20 in the Upper Thames, for

438   RX1day in the Calder and for the SDII ratio in the Coquet catchment. These indices evaluate the extremes,

439   which are inflated by the correction method (Cannon et al., 2015), and the precipitation intensity.

440   Considering the indices that are not based on the distribution, the Spearman correlation slightly

441   increases after GQM (Figs. 4c, S1c, S2c and S3c) whereas for the MSE the multi-model ensemble bias is

442   reduced, but there are cases when the biases of individual RCMs increase (Figs. 4c, S1c, S2c and S3c).

443   The same happens for the wet and dry spell lengths (Figs. 4b, S1b, S2b and S3b) and RX1day (Figs. 4c,

444   S1c, S2c and S3c). The multi-model bias spread from both resolutions is similar and smaller than 1 mm/day

445   up to the 90th percentile in all catchments (Fig. 5, second row). Above the 90th percentile, the spread of both

446   resolutions increases exponentially. The bias spread in the extremes is larger for the Glaslyn catchment

447   possibly as a consequence of the bias magnitude of the original uncorrected simulation (Fig. 5e).

448   **3.2.2.2.2.   Double Gamma distribution QM**

449   After applying the DGQM method, the skill with respect to distribution-based indices from all RCMs

450   at both resolutions becomes similar. The biases for most distribution-based indices are reduced compared

451   to both uncorrected and GQM. In all catchments, the biases are lower than 1 mm/day below the 99th

452   percentile after which biases increase. Thus, DGQM reduces the percentile biases in all catchments

453   compared to GQM. For the 90th precipitation percentile the DGQM approach increases the biases in all

454   catchments because at this percentile the method segments the precipitation distribution, generating an

455   increment in the bias. Nevertheless, this increase is approximately $\pm$ 1 mm/ day in all catchments except

456   the Glaslyn. Additionally, the simulation bias spread of both resolutions is similar for all catchments, as

457   expected (Fig. 5, last row).

458   For the extreme and precipitation intensity measures, DGQM reduces the biases compared to GQM

459   except for the RX1day and SDII ratio in the Upper Thames , R20 in the Glaslyn, R10 in the Calder and the

460   SDII ratio in the Coquet catchment. The simulation skill of the uncorrected models and the GQM and DGQM

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461 approaches is similar in all catchments for the Spearman daily correlation coefficient. Overall, the DGQM

462 provides outputs with smaller biases for most of the indices compared to the uncorrected and GQM

463 simulations.

464 **3.2.2.3. River flow**

465 **3.2.2.3.1. Gamma distribution QM**

466 River flow is simulated using the GQM precipitation and temperature as drivers. GQM decreases

467 the bias of all indices in every catchment, except for the Q10 in the upper Thames catchment (Fig. 6c). The

468 bias-corrected FDC simulation spread decreases for both resolutions in all catchments (Fig. 7, second row).

469 The observed FDC is completely included within the spread of both resolutions showing a good simulation

470 of the entire distribution.

471 From the pairwise indices, the skill of the multi-model ensemble improves for the monthly NSE (Fig.

472 6e) and the spread of the daily MSE is reduced in most cases. However, GQM can result in negative NSE

473 values for some models that had positive values when these were not bias-corrected (e.g. 0.44° RACMO

474 and HIRHAM in the Upper Thames). The Spearman correlation of daily time series increases slightly in all

475 cases (Fig. 6f, S4f, S5f and S6i).

476 **3.2.2.3.2. Double Gamma distribution QM**

477 The DGQM approach decreases the biases for all the distribution-based indices compared to both

478 uncorrected and GQM with the exception of Q95 for the Glaslyn catchment. Considering the non-

479 distribution-based indices, the NSE and MSE are not improved for the Coquet catchment. Even though the

480 biases are reduced, the simulation skill among all RCMs does not become similar for specific cases with

481 indices involving the extremes and the pairwise simulation (e.g. the Q10 annual frequency, Q10 and NSE

482 for the Upper Thames, Fig. 6b,c and e). Overall, the daily MSE and monthly NSE simulation skill improves

483 compared to the GQM approach. Thus implying that the river flow simulation skill is better when using the

484 DGQM. By construction of the bias correction method, the FDC simulation spread of both resolutions is

485 similar in shape and amplitude (Fig. 7, bottom row). Compared to GQM, the DGQM simulation spread is

486 further reduced.

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487   The Spearman correlation coefficient of the daily river flow time series increases slightly with not a

488   large difference compared to the GQM simulations. Overall, applying the DGQM approach results in smaller

489   biases compared to the GQM, in specific for the simulations of extremes and the monthly sequence.

4. Discussion

491   Regarding our first research question, as to whether the relative performance of the high- resolution

492   simulations is better than that of the lower-resolution simulations, the results show that the high-resolution

493   RCMs consistently have a better simulation skill for climate and river flow only in the Glaslyn catchment.

494   This is mainly because the size of this catchment is smaller than the 0.44° RCM cell, and it has a complex

495   topography and high precipitation. As a consequence, the skill of the 0.44° simulations in reproducing the

496   local physical features of this catchment is not good. For the other catchments, all of which are larger in

497   size and with less complex topography and less precipitation, both resolutions have a similar performance.

498   Similar results were obtained for the Upper Danube using HIRHAM at resolutions of 50 km x 50 km and 12

499   km x 12 km (Dankers et al., 2007). Only the skill of CCLM improved when using the high-resolution version.

500   Kotlarsky et al. (2014) found that CCLM also gave good results when simulating the mean, seasonal and

501   95th percentile of precipitation over the British Isles. In our study, the remaining RCMs did not improve their

502   simulation skill, implying that the high-resolution versions of these models do not accurately represent

503   processes occurring at higher resolutions.

504   The performance of the two RCM resolutions at simulating temperature was clearly linked to the

505   topographic characteristics of the study catchments. In the upper Thames and Calder catchments, which

506   have relatively flat topography, we found that there is no clear added value from the uncorrected high-

507   resolution RCMs; however, in the topographically-complex Glaslyn and Coquet catchments, all 0.11°

508   simulations outperformed their 0.44° version. These findings are similar to that of Onol et al. (2012) and

509   Tolika et al. (2016) and it is likely that they can be attributed to the difference in elevation from the grid cells

510   of the observations and models, and the lack of representation of the spatial variability. Increases in the

511   simulation skill of local climate when using higher-resolution simulations have been reported before,

512   particularly for mountainous regions (Evans et al., 2013; Larsen et al., 2013; Tolika et al., 2016).

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513   The uncorrected 0.11° simulations largely underestimate the precipitation and river flow

514   observations of the Glaslyn catchment, mainly due to the catchment's topographic complexity and high

515   levels of precipitation. Similar results for the Euro-CORDEX RCMs have been obtained for precipitation in

516   other regions with complex topography (e.g. Casanueva et al., 2016; Prein et al., 2015; Torma et al., 2015).

517   For the remaining catchments, the multi-model simulation spread of the simulations of both resolutions

518   includes the observed FDC, indicating that the models are able to provide useful simulations that resemble

519   the observed river flow. However, the simulation spread can be large; deviations in the annual mean river

520   flow reach almost 100% for some RCMs. Individual uncorrected RCMs have small biases and satisfactory

521   simulations of the river flow (e.g. 0.11° CCLM in the Calder and Coquet catchments), but there are also

522   RCMs that are not able to provide useful simulations. For example, the 0.11° RCA had the largest

523   precipitation and river flow biases in most indices for all catchments. In contrast, all the bias-corrected RCM

524   simulations are closer to the observed climate and river flow. Furthermore, the simulation skill from all bias-

525   corrected RCMs at both resolutions becomes similar and as a result, the simulation spread of the multi-

526   model ensemble is reduced compared to the uncorrected simulations, providing a smaller range of possible

527   scenarios.

528   Our results show that uncorrected RCMs provide river flow simulations that have too much spread

529   to be able to be used for impact studies (also stated by Kay et al., 2015; Cloke et al., 2013). Both resolutions

530   have a similar performance when simulating the seasonal mean river flow as there are biases from both

531   resolutions. However, certain high-resolution models tend to overestimate the seasonal flow largely for

532   most of the catchments and seasons (e.g. RCA in all catchments and HIRHAM in the Coquet and Calder

533   catchments). In contrast, the low-resolution CCLM underestimates river flow for all seasons and catchments.

534   For the medium-sized Calder catchment, individual models have different biases per season but the multi-

535   model ensemble mean shows a consistent underestimation for high-resolution models and underestimation

536   of river flow for the low-resolution modes. This is not distinguished in the larger Upper Thames nor in the

537   Coquet catchment. Similar to the annual mean flow, both resolutions underestimate the seasonal flow in

538   the Glaslyn catchment. In comparison, all the bias-corrected RCMs simulate the river flow much closer to

539   the observed flows and reduce the simulation spread, thus providing plausible inputs for impact studies.

540   Finally, to answer our last research question, we evaluate the simulation skill of DGQM compared

541   to GQM. Using four catchments with different characteristics, the DGQM provides a better simulation of the

542   river flow characteristics compared to the QGM approach, with a higher improvement for the simulation of

543   extremes and the monthly sequence. The GQM systematically reduces the precipitation bias up to the 90th

544   percentile, but exponentially increases the bias above this percentile. Therefore, to capture the properties

545   of extremes, we suggest using the DGQM with the 90th percentile as segmentation threshold in contrast to

546   Yang et al. (2010) who divided the distribution at the 95th percentile. Based on our results, the DGQM

547   reduces the precipitation and river flow biases of most indices compared to the commonly used GQM. This

548   is particularly relevant for the analysis of extreme precipitation and high flows as the GQM is usually

549   employed in flood analysis (e.g. Cloke et al., 2013) and river flow projections (e.g. Prudhomme et al., 2013).

550   In addition, the DGQM reduces the ensemble spread more than the GQM, without introducing much extra

551   complexity. However, no bias correction method will remove all biases. Thus, the selection of the method

552   depends on the requirements of each study (Nguyen et al., 2017) and it should be tested to evaluate

553   whether the benefits justify their calculation complexities.

554   Ideally, RCMs should not require post-processing techniques to provide simulations which can be

555   used with confidence (Ehret et al., 2012). However, our results demonstrate large biases for various

556   diagnostic indices for the reanalysis-driven RCMs. Particular RCMs provide plausible river flow simulations,

557   for instance, 0.11° CCLM for the Calder catchment when assessing the annual and seasonal means, low

558   flows, high flow occurrence and pairwise indices. However, the RCM simulation skill is catchment-

559   dependent. Thus, at the moment, bias correction seems to be the best approach to reduce the ensemble

560   spread and its biases. Nevertheless, bias correction methods should be used carefully for the analysis of

561   future projections (Cloke et al., 2013) as bias correction cannot correct fundamental problems from the

562   original climate model (Maraun and Widmann, 2015; Maraun et al., 2017) and the spread of the bias-

563   corrected simulations might not reflect the total real uncertainty. Climate research is focusing on

564   determining the causes behind the biases (e.g. Addor et al., 2016) and improving the simulation of the

565   processes (e.g. Zittis et al., 2017; Meredith et al., 2015). For instance, convection permitting models seek

566   to improve the simulation of precipitation extremes (Tölle et al., 2017; Gutjahr et al., 2016). However, the

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567   computational cost of developing such models is large and, as a consequence, the simulation length is

568   short and the availability of GCM-RCM projections is low.

569   By analysing four catchments with different characteristics, we evaluate the RCM simulation skill in

570   different contexts. Our results suggest that the small size and the high precipitation (e.g. Glaslyn catchment)

571   are the main factors related to the better simulation skill from the high-resolution RCMs over the low-

572   resolution models for the simulation of river flow. The importance of topographical complexity and other

573   characteristics for the simulation outputs is secondary. This is highlighted by the results of the medium-

574   sized Coquet catchment, for which both resolutions have similar simulation skill even with its complex

575   topography. Although the hydrological model used (HEC-HMS) was chosen as it has been used before in

576   assessment of climate change impacts (e.g. Babel et al., 2014; Azmat et al., 2015) and acknowledging that

577   there are a diversity of methods used to simulate the hydrological processes, we note that our results are

578   unlikely to substantially change when using other hydrological model. We support our statement as we

579   assess the performance of the different resolutions by evaluating the RCM outputs as well as the

580   hydrological model outputs, both giving similar results. An assessment of the hydrological model uncertainty

581   is beyond the scope of this study, but will be the subject of future work.

5. Conclusions

583   This study provides information on the added value from increasing RCM resolution and bias

584   correction techniques for the simulation for river flow. Previous studies have assessed the improvement in

585   the simulation skill of climate variables due to an increase in the RCM resolution, but this might not

586   guarantee an improvement in the simulation of the river flow parameters that are relevant for impact studies.

587   We conducted a comprehensive analysis on how the uncorrected and bias-corrected RCM outputs drive

588   the simulations of river flow at high and low resolutions. Each RCM used here has the same

589   parameterisation, domain and driving data at both resolutions, and therefore the comparison only evaluates

590   the effect of increasing its resolution. We analysed four catchments located at different latitudes within

591   Great Britain. These catchments vary in climate (e.g. precipitation ranging from 2900 mm yr^{-1} to 762 mm

592   yr^{-1}), physical characteristics (flat and complex topographies, areas ranging from 69 km^2 to 1616 km^2), land

593   use (varying from urban-dominant to agricultural and natural areas) and hydrological characteristics (e.g.

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594   annual mean river flow ranging from 15.3 m^3 s^{-1} to 5.8 m^3 s^{-1}). We applied a detailed assessment of the

595   simulation skill of the climate and hydrological models using a set of indices relevant for the analysis of

596   different impacts.

597   We show that the uncorrected 0.11° RCMs only showed better skill in simulating precipitation and

598   river flow in the small catchment. This is because the spatial resolution of the 0.44° models is four-times

599   larger than the catchment size, whereas one cell of the 0.11° model is similar in area to the catchment.

600   Nevertheless, the high-resolution simulations are not able to accurately represent the complex topography

601   of this catchment and do not resolve local processes, underestimating the observed precipitation and the

602   entire FDC. In Australia, Parana Manage et al. (2016) also found that the averaging of topography of gridded

603   outputs influences on the accurate simulation of rainfall.

604   Both resolutions capture the temperature and precipitation distribution, as well as the FDC, for the

605   remaining sites. Thus, in principle, the simulations could be used for climate change assessments.

606   Nevertheless, for most of the indices, the multi-model variability is large (e.g. the mpe of the annual mean

607   river flow simulation ranges from 198% to -31% in the Upper Thames, with an average of 49%), making

608   any interpretation difficult in practice. Only one RCM (CCLM) improves the river flow simulation when using

609   its high-resolution version in all catchments, implying that the remaining models do not simulate the relevant

610   high-resolution processes accurately as there is no consistent difference between their high and low

611   resolution versions. Therefore, there is no added value from using the high-resolution RCMs in those

612   catchments for the assessment of river flow impacts.

613   Bias-correction reduces the distribution-based biases for all RCMs and resolutions by construction.

614   Thus, the bias-corrected high- and low-resolution RCMs have similar simulation skill for the distribution-

615   based indices. There is also less spread from the ensemble simulation of precipitation and river flows (e.g.

616   the mpe of the annual mean river flow simulations for the Upper Thames ranges from -1% to 16% when

617   corrected using DGQM, with an average of 7%). Nevertheless, daily pairwise indices, which assess the skill

618   of the model when simulating the observed time series, are not improved by bias correction. However, the

619   monthly NSE results indicate that bias correction can improve the pairwise simulation on monthly

620   timescales. Overall, correcting the RCMs to the local temperature and precipitation provides a reduction of

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621   the ensemble spread, making the outputs more useful for the analysis of impacts. Nevertheless, it should

622   be considered that the ensemble spread of uncorrected and corrected models can underestimate the true

623   simulation uncertainty.

624   In comparison to GQM, DGQM provides a larger reduction in the simulation biases for precipitation

625   and river flow. The main difference between both methods is the greater correction from DGQM for

626   precipitation extremes (95th percentile, R10, R20, R95p) and high flows (Q10 and Q10 annual frequency).

627   The monthly NSE consistently shows an improvement in the simulation skill of RCMs that are corrected

628   using DGQM. Overall, for most of the RCMs and considering the results from all indices, the DGWM

629   outperforms GQM.

630   Our study shows that an increase in RCM resolution does not always imply a better simulation of

631   hydrological impacts, especially for large catchments. In contrast, small catchments with complex

632   topography are still difficult to be simulated accurately by high-resolution models, concurring with Dankers

633   et al (2007). The uncorrected RCM ensemble generally provides a large spread which makes it difficult to

634   use for impact assessment. Similar outcomes have been obtained for other regions, for example Australia

635   (Lockart et al. 2016), Canada and China (Wang et al. 2019). Bias-correction provides an alternative to

636   reduce the biases and multi-model spread, making decision-making easier. From the methods evaluated

637   here, DGQM reduces most of the RCM biases without much more complexity added to the bias-correction

638   method employed when using GQM. However, and agreeing with Cloke et al. (2013), Huang et al. (2014)

639   and Lockart et al. (2016), the bias-corrected outputs should be used carefully when evaluating changes in

640   very extreme flows as the correction inflates the simulated extremes. Compared to previous studies, we

641   can state that our results are robust as we included a larger number of RCMs with different

642   parameterisations for our analysis.

643   Whilst effective, bias correction adds extra uncertainty to the analysis chain (Cloke et al., 2013;

644   Rummukainen, 2016). Therefore, it must be used with consideration of its limitations: dependence on the

645   training period (Lafon et al., 2013), assumption of temporal stability of the correction function (Chen et al.,

646   2015), issues of sub-grid variability and inflation of variance (Maraun, 2013), inter-variable consistency

647   (Wilcke et al., 2013), spatial representation over complex terrain (Maraun and Widmann, 2015) and biases

648 from the driving data (Maraun et al., 2017). The extent to which the climate change signal is altered must

649 also be considered (Maraun, 2013; Velázquez et al., 2015) along with the possibility that bias correction

650 can produce larger biases for extremes than for the mean (Huang et al., 2014). Additionally, we

651 acknowledge that using different data to drive the RCMs used in this study, for instance a GCM, could give

652 different results, as could the use of a different hydrological model.

653 Our results can provide an insight on whether RCMs of high(er) resolution improve the simulation skill.

654 These can be useful for regions of similar characteristics where high(er)-resolution RCMs have not been

655 developed yet and would require considerable time and effort to be produced. If used, bias-correction

656 methods should be tested for the specific analysis that will be performed. This study provided different

657 methods to perform this testing for the different RCMs and bias-correction methods for climatology and

658 hydrology.

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660 **Acknowledgements**

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669 **Tables**

670 Table 1. Characteristics of the study sites

	Upper Thames	Glaslyn	Calder	Coquet
Area (km^2)	1616	69	316	346
Maximum elevation (masl[1])	330	1080	556	775
Minimum elevation (masl[1])	52	30	40	71
Mean annual precipitation (mm/year)	762	2957	1251	968
Mean annual temperature (°C)	9.7	8.1	8.4	7.4
Mean annual PET (mm/yr)	522	477	486	473
Mean annual river flow (m^3/s)	15.3	5.8	8.8	6.1

Precipitation 90th percentile (mm/day)	6.7	24.4	10.3	7.7
Precipitation 95th percentile (mm/day)	10.2	34.2	14.8	11.9
[2]Q10 (m³/s)	34.8	13.5	19.9	12.4
[3]Q95 (m³/s)	1.90	0.55	1.99	0.84

671   [1] Meters above the sea level

672   [2] River flow that is exceeded for 10% of the daily river flow time series

673   [3] River flow that is exceeded for 95% of the daily river flow time series

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676   Table 2. RCMs used in this study

RCM	Institute	Period	Reference
CCLM-CLMCOM	Brandenburg University of Technology (BTU)	1989-2008	Böhm et al., 2006; Rockel et al., 2008
HIRHAM 5	Danish Meteorological Institute (DMI)	1989-2008	Christensen et al., 1998
RACMO22E	Royal Netherlands Meteorological Institute (KNMI)	1979-2008	Van Meijgaard et al., 2012
RCA4	Swedish Meteorological and Hydrological Institute (SMHI)	1984-2008	Samuelsson et al., 2011
WRF 3.3.1	Institute Pierre Simon Laplace (IPSL) and Institute National de l'Environment Industriel et des Risques (INERIS)	1989-2008	Skamarock et al., 2008

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Table 3. Description of the precipitation, temperature and river flow indices used in this study

Index	Description	Performance measure
Precipitation		
95th percentile	A measure of very extreme events: 95th percentile of daily precipitation	Bias (mm/day)
90th percentile	A measure of extreme events: 90th percentile of daily precipitation	Bias (mm/day)
50th percentile	50th percentile of daily precipitation	Bias (mm/day)
25th percentile	25th percentile of daily precipitation	Bias (mm/day)
[a] Wet spell length	Mean wet spell length for a given month of the year	Bias (days)
[a] Dry spell length	Mean dry spell length for a given month of the year	Bias (days)
[a] Annual mean precipitation	Annual accumulated precipitation	Mean percentage error
[a] Monthly mean precipitation	Accumulated precipitation for a given month of the year	Mean percentage error
[b] Relative daily MSE	Mean daily square error, shown as ratio to the largest MSE result (considering both corrected and uncorrected RCMS)	MSE (ratio)
[b] Spearman correlation coefficient	Spearman correlation coefficients between the daily simulated and observed time series	Index
[a] Maximum one day precipitation (RX1day)	Maximum one-day precipitation for a given month of the year	Mean percentage error
[a] Simple Daily Intensity Index (SDII)	Ratio of the annual total precipitation to the number of wet days (≥ 1 mm) in all years	Index
[a] Number of heavy precipitation days (R10)	Mean number of days with precipitation $\geq$ 10mm within a year	Bias (days)
[a] Number of very heavy precipitation days (R20)	Mean number of days with precipitation $\geq$ 20mm within a year	Bias (days)
[a] Very wet days (R95p)	Mean annual accumulated precipitation from days > 95th percentile in all years	Mean percentage error
Temperature		
[a] Annual mean temperature	Annual mean temperature over the validation period	Mean percentage error
[a] Monthly mean temperature	Monthly mean temperature	Mean percentage error
99th percentile of daily mean temperature	99th percentile of the daily mean temperature	Bias (°C/day)
1st percentile of daily mean temperature	1st percentile of the daily mean temperature	Bias (°C/day)
[b] Pearson correlation coefficient	Pearson correlation coefficient between the daily RCM and observation time series	Index
River Flow		
Q10	A measure of high flows: river flow that is exceeded for 10% of the daily river flow time series	Bias (m^3/s)
Q95	A measure of low flows: river flow that is exceeded for 95% of the daily river flow time series	Bias (m^3/s)
[a] Annual Q10 frequency	Mean number of days for which the observed Q10 is exceeded within a year	Bias (days)
[a] Annual mean river flow	Annual mean daily river flow over the validation period	Mean percentage error
[a] Winter (DJF) mean river flow	Winter mean daily river flow over the validation period	Mean percentage error
[a] Spring (MAM) mean river flow	Spring mean daily river flow over the validation period	Mean percentage error
[a] Summer (JJA) mean river flow	Summer mean daily river flow over the validation period	Mean percentage error
[a] Autumn (SON) mean river flow	Autumn mean daily river flow over the validation period	Mean percentage error
[b] Monthly NSE	Monthly Nash Sutcliffe Efficiency index	Index
[b] Relative daily MSE	Mean daily square error, shown as ratio to the largest MSE result (considering both corrected and uncorrected RCMS)	MSE (ratio)
[b] Spearman correlation coefficient	Spearman correlation coefficient between the daily simulated and observed time series	Index

[a] Estimated using the long term mean (one value over the entire series)

[b] Estimated considering the time series values (one value per time step)

680   Table 4. Indices from the calibration and validation of the hydrological models
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Catchment	Step	Period	Daily NSE	Q10 bias		Q95 bias	
				(m³/s)	(%)	(m³/s)	(%)
Upper Thames	Calibration	1986-2010	0.70	-2.1	-6	-0.45	-25
	Validation	1961-1985	0.57	1.5	5	-0.90	-44
Glaslyn	Calibration	1991-2010	0.78	1.0	8	-0.07	-11
	Validation	1971-1990	0.78	0.7	5	-0.03	-6
Calder	Calibration	1994-2010	0.62	1.5	8	-0.31	-16
	Validation	1976-1993	0.60	1.3	7	-0.24	-12
Coquet	Calibration	1992-2010	0.63	1.3	11	-0.24	-27
	Validation	1973-1991	0.52	-0.6	-5	-0.25	-31

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708 Table 5. RCM rank for the temperature indices for each catchment: 1 = best, 10 = worst. The asterisks (*)
709 indicate the resolution with the best simulation skill of each RCM in each catchment

		99th percentile	1st percentile	Annual mean	Monthly mean	Correlation	Average score	Ranking	
Upper Thames	0.11°CCLM	10	7	2	9	1	5.8	6	*
	0.11°HIRHAM	3	9	3	5	6	5.2	5	
	0.11°RACMO	2	8	9	7	4	6.0	7	
	0.11°RCA	7	5	10	10	5	7.4	10	
	0.11°WRF	4	1	5	4	8	4.4	2	*
	0.44°CCLM	9	10	1	8	2	6.0	7	
	0.44°HIRHAM	1	6	4	3	9	4.6	3	*
	0.44°RACMO	5	4	7	2	3	4.2	1	*
	0.44°RCA	8	2	6	1	7	4.8	4	*
	0.44°WRF	6	3	8	6	10	6.6	9	
Glaslyn	0.11°CCLM	9	2	4	3	1	3.8	3	*
	0.11°HIRHAM	7	6	2	4	7	5.2	5	*
	0.11°RACMO	3	7	1	1	4	3.2	1	*
	0.11°RCA	2	4	3	2	6	3.4	2	*
	0.11°WRF	4	8	5	6	10	6.6	7	*
	0.44°CCLM	10	1	6	5	2	4.8	4	
	0.44°HIRHAM	8	3	8	7	9	7.0	8	
	0.44°RACMO	5	5	7	8	3	5.6	6	
	0.44°RCA	6	9	9	9	5	7.6	9	
	0.44°WRF	1	10	10	10	8	7.8	10	
Calder	0.11°CCLM	9	7	8	8	1	6.6	7	
	0.11°HIRHAM	5	9	7	7	5	6.6	7	
	0.11°RACMO	8	10	10	10	4	8.4	9	
	0.11°RCA	10	8	9	9	6	8.4	9	
	0.11°WRF	7	3	1	4	8	4.6	4	*
	0.44°CCLM	6	6	6	5	2	5	5	*
	0.44°HIRHAM	4	2	2	1	9	3.6	2	*
	0.44°RACMO	2	4	5	2	3	3.2	1	*
	0.44°RCA	3	1	4	3	7	3.6	2	*
	0.44°WRF	1	5	3	6	10	5	5	
Coquet	0.11°CCLM	9	2	2	3	2	3.6	3	*
	0.11°HIRHAM	1	3	3	2	5	2.8	1	*
	0.11°RACMO	3	7	9	7	4	6.0	5	*
	0.11°RCA	7	6	8	4	6	6.2	6	*
	0.11°WRF	5	1	1	1	8	3.2	2	*
	0.44°CCLM	4	4	7	5	1	4.2	4	
	0.44°HIRHAM	10	8	5	6	9	7.6	9	
	0.44°RACMO	6	9	6	9	3	6.6	8	
	0.44°RCA	2	5	10	8	7	6.4	7	
	0.44°WRF	8	10	4	10	10	8.4	10	

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711   Table 6. RCM rank for precipitation: 1-best, 10-worst. The asterisks (*) indicate the resolution with the best simulation skill of each RCM in each catchment

		Pr 95th	Pr 90th	Pr 50th	Pr 25th	Annual Mean	Monthly MSE	Dry Spell	Wet Spell	Monthly Mean	Correl.	SDII	R10	R20	R95p	RX1day	Average score	Ranking	
Upper Thames	0.11°CCLM	8	5	1	2	5	2	1	4	5	1	6	8	4	8	2	4.1	1	*
	0.11°HIRHAM	7	4	4	3	3	5	6	6	1	3	5	7	6	3	7	4.7	4	
	0.11°RACMO	3	2	9	8	7	3	4	5	4	10	9	3	5	5	9	5.7	8	
	0.11°RCA	10	10	10	10	10	10	10	10	10	6	2	10	10	10	8	9.1	10	
	0.11°WRF	1	1	6	7	6	8	7	3	8	5	7	1	3	1	3	4.5	2	*
	0.44°CCLM	9	9	2	1	8	4	3	8	7	2	4	9	8	9	1	5.6	7	
	0.44°HIRHAM	5	6	3	5	2	7	5	9	3	7	3	4	1	4	5	4.6	3	*
	0.44°RACMO	4	3	5	6	4	1	2	2	2	9	8	5	7	6	6	4.7	4	*
	0.44°RCA	2	8	8	4	9	9	9	1	9	4	1	2	1	2	4	4.9	6	*
	0.44°WRF	6	7	7	9	1	6	8	7	6	8	10	6	9	7	10	7.1	9	
Glaslyn	0.11°CCLM	5	5	8	2	5	5	6	5	5	1	5	5	5	5	5	4.8	5	*
	0.11°HIRHAM	1	1	6	5	1	3	5	3	2	3	1	3	1	1	1	2.5	1	*
	0.11°RACMO	3	3	3	9	3	1	3	8	3	2	3	2	3	2	4	3.5	3	*
	0.11°RCA	2	2	2	10	2	2	8	6	1	6	2	1	2	3	2	3.4	2	*
	0.11°WRF	4	4	1	6	4	4	4	4	4	7	4	4	4	4	3	4.1	4	*
	0.44°CCLM	10	9	10	3	9	9	9	9	9	5	9	9	9	8	7	8.3	9	
	0.44°HIRHAM	9	10	9	1	10	10	10	10	10	9	7	10	10	9	9	8.9	10	
	0.44°RACMO	7	7	4	7	7	7	2	1	7	4	10	7	7	7	8	6.1	7	
	0.44°RCA	8	8	7	4	8	8	7	7	8	8	8	8	8	10	10	7.8	8	
	0.44°WRF	6	6	5	8	6	6	1	2	6	10	6	6	6	6	6	5.7	6	
Calder	0.11°CCLM	1	2	2	1	1	1	2	3	1	1	1	2	2	2	9	2.1	1	*
	0.11°HIRHAM	10	10	8	5	9	9	7	8	9	5	7	9	10	10	10	8.4	9	
	0.11°RACMO	2	1	9	9	3	5	5	9	4	4	4	1	1	1	3	4.1	2	*
	0.11°RCA	9	9	10	10	10	10	10	10	10	6	3	10	9	9	1	8.4	9	
	0.11°WRF	3	3	6	4	6	8	6	5	7	8	2	4	3	3	8	5.1	5	*
	0.44°CCLM	6	7	4	2	8	3	4	4	8	2	5	7	4	6	2	4.8	3	
	0.44°HIRHAM	4	4	1	3	7	4	9	6	6	7	6	3	5	4	5	4.9	4	*
	0.44°RACMO	8	8	7	7	5	2	3	1	3	3	10	8	8	8	6	5.8	7	
	0.44°RCA	7	6	3	6	4	7	8	2	5	9	8	6	7	7	7	6.1	8	*
	0.44°WRF	5	5	5	8	2	6	1	7	2	10	9	5	6	5	4	5.3	6	
Coquet	0.11°CCLM	4	5	1	1	2	1	1	3	1	1	3	4	2	1	2	2.1	1	*
	0.11°HIRHAM	6	9	9	7	9	9	9	7	9	5	1	7	5	6	4	6.8	8	
	0.11°RACMO	5	3	6	8	1	3	7	5	2	4	9	5	4	5	5	4.8	4	*
	0.11°RCA	10	10	10	10	10	10	10	10	10	9	7	10	9	10	1	9.1	10	
	0.11°WRF	2	1	5	3	3	6	5	6	3	7	5	2	1	2	3	3.6	2	*
	0.44°CCLM	7	6	4	2	8	4	3	8	7	2	3	6	7	7	6	5.3	6	
	0.44°HIRHAM	3	2	8	9	4	5	8	2	4	8	1	1	3	4	8	4.7	3	*
	0.44°RACMO	8	7	3	4	6	2	2	4	6	3	9	8	10	9	10	6.1	7	
	0.44°RCA	1	4	7	5	5	8	6	1	5	6	7	3	6	3	7	4.9	5	*
	0.44°WRF	9	8	2	6	7	7	4	9	8	10	5	9	8	8	9	7.3	9	

Table 7. RCM rank for river flow: 1-best, 10-worst. The asterisks (*) indicate the resolution with the best simulation skill of each RCM in each catchment

		Annual mean	Winter mean	Spring mean	Summer mean	Autumn mean	Monthly NSE	Daily MSE	Correl.	Q10	Q10 frequency	Q95	Average score	Rank	
Upper Thames	0.11° CCLM	1	2	2	3	3	1	1	4	1	1	1	1.8	1	*
	0.11° HIRHAM	3	4	4	2	1	3	3	1	3	3	4	2.8	2	*
	0.11° RACMO	8	9	8	6	9	9	8	7	8	8	9	8.1	9	
	0.11° RCA	10	10	10	10	10	10	10	10	10	10	10	10.0	10	
	0.11° WRF	7	1	6	9	5	6	6	8	5	6	8	6.1	6	*
	0.44° CCLM	4	7	1	4	7	2	2	3	6	4	3	3.9	4	
	0.44° HIRHAM	2	5	3	1	2	4	5	5	2	2	2	3.0	3	
	0.44° RACMO	5	6	5	5	6	5	4	2	4	5	7	4.9	5	*
	0.44° RCA	9	8	9	7	8	8	9	6	9	9	6	8.0	8	*
	0.44° WRF	6	3	7	8	4	7	7	9	7	7	5	6.4	7	
Glaslyn	0.11° CCLM	5	5	5	6	6	5	5	4	5	5	8	5.36	5	*
	0.11° HIRHAM	1	1	1	4	1	1	3	2	1	1	4	1.82	1	*
	0.11° RACMO	2	2	2	3	3	2	1	1	2	2	2	2	2	*
	0.11° RCA	3	3	3	1	2	3	2	6	3	3	1	2.73	3	*
	0.11° WRF	4	4	4	2	4	4	4	5	4	4	3	3.82	4	*
	0.44° CCLM	9	9	10	10	10	9	9	8	10	8	9	9.18	9	
	0.44° HIRHAM	10	10	9	9	9	10	10	9	9	8	10	9.36	10	
	0.44° RACMO	7	6	7	8	7	7	7	3	7	7	6	6.55	7	
	0.44° RCA	8	8	8	7	8	8	8	10	8	10	7	8.18	8	
	0.44° WRF	6	7	6	5	5	6	6	7	6	6	5	5.91	6	
Calder	0.11° CCLM	2	2	6	4	5	2	1	2	1	1	1	2.45	2	*
	0.11° HIRHAM	9	10	9	8	9	9	9	4	9	9	9	8.55	9	
	0.11° RACMO	6	6	7	6	6	5	6	3	6	8	8	6.09	6	
	0.11° RCA	10	9	10	10	10	10	10	9	10	10	10	9.82	10	
	0.11° WRF	7	8	8	9	2	8	8	6	7	7	7	7	8	
	0.44° CCLM	8	5	5	7	8	6	3	5	8	6	6	6.09	6	
	0.44° HIRHAM	5	4	3	5	7	4	5	10	5	5	4	5.18	5	*
	0.44° RACMO	3	3	2	1	1	1	2	1	3	2	2	1.91	1	*
	0.44° RCA	4	7	4	3	3	7	7	8	4	4	5	5.09	4	*
	0.44° WRF	1	1	1	2	4	3	4	7	2	3	3	2.82	3	*
Coquet	0.11° CCLM	1	5	1	1	6	4	5	1	4	1	1	2.73	1	*
	0.11° HIRHAM	9	6	9	9	8	9	9	5	8	9	9	8.18	9	
	0.11° RACMO	7	1	7	7	5	6	3	6	2	2	8	4.91	5	
	0.11° RCA	10	10	10	10	10	10	10	10	10	10	10	10	10	
	0.11° WRF	2	2	2	5	2	2	6	4	1	3	5	3.09	2	*
	0.44° CCLM	8	9	8	4	9	7	2	2	9	8	2	6.18	7	
	0.44° HIRHAM	6	3	4	8	7	8	8	9	5	7	7	6.55	8	*
	0.44° RACMO	3	7	3	2	3	1	1	3	6	6	4	3.55	3	*
	0.44° RCA	5	4	6	6	4	5	7	7	3	4	6	5.18	6	*
	0.44° WRF	4	8	5	3	1	3	4	8	7	5	3	4.64	4	

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955

956 Figure 1. Location of the study catchments (outlet marked with a triangle) and the RCM grid boxes used for their
957 simulation. The 0.11° and 0.44° grid boxes are shown with solid and dashed lines, respectively
958

959 Figure 2. Results of the temperature performance measures, described on Table 3, for the a) upper Thames, b) Glaslyn, c)
960 Calder and d) Coquet catchments. Filled symbols represent the 0.11° RCMs and empty symbols represent the 0.44° RCMs.
961 Please note the differences in the y-axis (BC = Bias corrected)
962

963 Figure 3. Temperature percentile biases for the uncorrected and bias-corrected RCMs. The solid fill represents the spread
964 form the 0.44° RCMs and the dotted fill is the spread from the 0.11° RCMs
965

966 Figure 4. Results of the precipitation performance measures for the upper Thames catchment. Filled symbols represent
967 the 0.11° RCMs and empty symbols represent the 0.44° RCMs. Please note the differences in the y-axis. For definitions of
968 the performance measures refer to Table 3 (BC-1G = Bias corrected using the Gamma distribution QM approach, BC-2G =
969 Bias corrected using the Double Gamma distribution approach)

970 Figure 5. Precipitation percentile biases for the uncorrected and bias-corrected RCMs using the Gamma distribution
971 (GQM) and Double Gamma distribution (DGQM) QM. The solid fill represents the spread of the 0.44° RCMs and the dotted
972 fill the spread of the 0.11° RCMs. The 90th precipitation percentile is represented by a vertical dotted line
973

974 Figure 6. Results of the river flow performance measures for the upper Thames catchment. Filled symbols represent the
975 0.11° RCMs and empty symbols represent the 0.44° RCMs. Please note the differences in the y-axis. For definitions of the
976 performance measures refer to Table 3 (GQM = Gamma distribution Quantile Mapping and DGQM = double Gamma
977 distribution Quantile Mapping)
978

979 Figure 7. Flow duration curve biases from using the uncorrected and bias-corrected temperature and precipitation
980 simulations. The 0.44° RCMs spread is shown with a solid fill, the 0.11° RCMs spread with a dotted fill and the reference
981 FDC with a solid line. (GQM = Gamma distribution Quantile Mapping and DGQM = double Gamma distribution Quantile
982 Mapping)
983

984 Figure S1. Similar to Figure 5 but for the Glaslyn catchment
985

986 Figure S2. Similar to Figure 5 but for the Calder catchment
987

988 Figure S3. Similar to Figure 5 but for the Coquet catchment
989

990 Figure S4. Similar to Figure 7 but for the Glaslyn catchment
991

992 Figure S5. Similar to Figure 7 but for the Calder catchment
993

994 Figure S6. Similar to Figure 7 but for the Coquet catchment
995

996

997

998

999 • 0.11° and 0.44° RCMs are compared in four catchments using climate and flow indices

1000 • The 0.11° simulations had superior skill in one catchment with complex topography

1001 • The RCM flow simulation range is large for all catchments at both resolutions

1002 • Bias correction improves the monthly but not the daily temporal variability

1003 • Double Gamma quantile mapping outperforms the single Gamma quantile mapping

1004

1005

1006 **Declaration of interests**

1007

1008 ☒ The authors declare that they have no known competing financial interests or personal relationships that
1009 could have appeared to influence the work reported in this paper.

1010

1011 ☐The authors declare the following financial interests/personal relationships which may be considered as
1012 potential competing interests:
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1019 Author statement

1020   Pasten-Zapata: Funding acquisition, conceptualization, methodology, investigation, formal analysis and writing
1021   original-draft

1022   Jones: Conceptualization, resources, writing original-draft, writing review and editing, supervision

1023   Moggridge: Conceptualization, resources, writing original-draft, writing review and editing, supervision

1024   Widmann: Conceptualization, writing original-draft, writing review and editing

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