



# Differences in hydrological impacts using regional climate model and nested convection-permitting model data

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## Abstract

Assessing the potential impacts of climate change on river flows is critically important for adaptation. Data from global or nested regional climate models (GCMs/RCMs) are frequently used to drive hydrological models, but now there are also very high-resolution convection-permitting models (CPMs). Here, data from the first CPM climate ensemble for the UK, along with the RCM ensemble within which the CPM is nested, are used to drive a grid-based hydrological model. The performance for simulating baseline (1981–2000) river flows is compared between the RCM and the CPM, and the projections of future changes in seasonal mean flows and peak flows are compared across Britain (1981–2000 to 2061–2080). The baseline performance assessment shows that (before bias correction) the CPM generally performs better than the RCM, and bias correction of precipitation makes both the RCM and CPM perform more similarly to use of observation-based driving data. The analysis of future changes in flows shows that the CPM almost always gives higher flow changes than the RCM. If reliable, these differences in flow projections suggest that adaptation planning for high flows based on use of regional data may be insufficient, although planning for low flows may be slightly over-cautious. However, the availability of CPM data only for one RCM/GCM is a limitation for use in adaptation as it under-samples the uncertainty range. There are significant challenges to the wider application of CPM ensembles, including the high computational and data storage demands.

**Keywords** Climate change · Hydrological impacts · UK Climate Projections 2018 · UKCP18 · CPM · RCM

## 1 Introduction

Data from global climate models (GCMs) or nested regional climate models (RCMs) are frequently used to drive hydrological models to investigate the potential impacts of climate change on river flows (e.g. Roudier et al. 2016; Marx et al. 2018; Thober et al. 2018; Zhai et al. 2020). GCMs and RCMs have typical horizontal resolutions of hundreds down to tens

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of kilometres, so data typically require some form of further spatial downscaling before use for finer-scale hydrological impact modelling (e.g. Kay et al. 2009).

Computing advances have recently enabled the application of higher-resolution ‘convection-permitting’ models (CPMs), commonly used in weather forecasting, for climate change projections (Kendon et al. 2021a). CPMs have horizontal resolutions ranging from ~5 km down to a few hundred metres (Fosser et al. 2020). This finer resolution means that such models can simulate the atmosphere at a scale closer to that of convection, so they do not require schemes parameterising convective storms; lower-resolution models rely on such schemes, which represent the average effect of convection and can thus be a significant source of uncertainty (Kendon et al. 2021a). The finer resolution also means that CPMs better represent landscape details such as coastlines, orography, and urban areas (Kendon et al. 2021a; Lucas-Picher et al. 2021). Like RCMs, CPMs are typically applied as limited area models, which need to be provided with initial and lateral boundary conditions. For producing climate projections, CPMs are nested within (i.e. take their boundary conditions from) a coarser-resolution climate model, which can be a GCM, or an RCM nested within a GCM (‘telescopic nesting’; Lucas-Picher et al. 2021).

CPMs have been run for various regions around the globe, and their added value quantified in terms of meteorological performance (Lucas-Picher et al. 2021; Kendon et al. 2021a), but their value for hydrological impacts has been less studied (Lucas-Picher et al. 2021). Analyses using CPMs for assessing climate change impacts on river flows include catchments in Texas (Qing et al. 2020), Norway (Schaller et al. 2020) and the Eastern Alps (Reszler et al. 2018). Schaller et al. (2020) suggest that use of higher-resolution CPM data is necessary for flood modelling in Norway because of the CPM’s improved representation of orographic precipitation, but Reszler et al. (2018) found no clear added value from use of CPM data compared to RCM data for flood modelling in the Alps. Furthermore, there are significant challenges to CPM implementation and application, including the heavy computational and data storage demands which limit domain size, time-slice length and/or ensemble size (Lucas-Picher et al. 2021; Kendon et al. 2021a).

The first decadal-length climate change runs of a CPM for southern Britain (Kendon et al. 2014) were used to drive a grid-based hydrological model (Kay et al. 2015). Analysis of simulated river flows showed that the nested 1.5-km CPM gave greater increases in flood peaks than the 12-km RCM in spring and winter in particular. However, in the above study only a single CPM was available (not an ensemble), for relatively short time-slices (~13 years baseline and future). Also, the CPM performance for baseline flows was generally worse than the RCM (driven by re-analysis boundary conditions), likely due to the tendency of the CPM to produce heavy rainfall that was too intense (Kendon et al. 2012).

As part of UK Climate Projections 2018 (UKPC18; Lowe et al. 2018), a 12-member ensemble of 2.2-km CPM projections was produced for the UK, nested in an ensemble of 12-km RCM projections (Kendon et al. 2021b). As well as providing an ensemble for the whole of the UK, the latest CPM projections are available for three 20-year periods, thus representing a significant advance despite having a slightly lower spatial resolution. A 2.2-km grid was chosen, rather than the previous 1.5-km grid, as a compromise between the (relatively small) added value and significantly higher computational cost of increasing resolution (Fosser et al. 2020). There have also been changes to model physics which have improved performance relative to previous versions, including the tendency for heavy rainfall to be too intense (Fosser et al. 2020).

Previous application of the UKCP18 RCM ensemble has suggested large decreases in summer and extreme low flows across Britain, but possible increases in winter and extreme high flows, especially in the north and west (Kay 2021; Lane & Kay 2021). The main

reason for developing CPM projections in the UK was to enable investigation of potential future changes in extreme summer storms (Orr et al. 2021). But analysis shows greater increases in winter precipitation in the CPM than in the driving RCM (Kendon et al. 2021b Fig. 4.2.3), due to increased formation of winter convective events over the sea and their advection inland. Since winter is the main flood season across much of Britain (Ledingham et al. 2019), differences between CPM and RCM winter precipitation changes could be important for flood impacts.

Using data from the UKCP18 RCM and CPM ensembles to drive a national-scale grid-based hydrological model, the main aim of this study is to compare RCM- and CPM-based projections of future changes in seasonal mean flows and peak flows across Great Britain (GB). The performance of RCM and CPM data for simulating baseline flows is also compared.

## 2 Methods

### 2.1 Hydrological model and observation-based driving data

Grid-to-Grid (G2G) is a grid-based runoff-production and routing model with an optional snow module which usually operates across GB on a 1-km grid at a 15-min time-step (Bell et al. 2009, 2016). Runoff from each grid cell forms the lateral inflows to the grid-based flow routing scheme, and flow is routed from grid cell to grid cell along flow pathways. The model simulates natural rather than gauged flows and has been shown to perform well for a wide range of catchments (Bell et al. 2009, 2016; Rudd et al. 2017; Formetta et al. 2018). Inclusion of abstraction and discharge data typically improves model performance in affected catchments (Rameshwaran et al. 2022), but limited data availability means that such artificial influences are not included here.

Gridded precipitation, potential evaporation (PE) and temperature time-series are required to drive G2G (including the snow module). An observation-based simulation for December 1980–November 2000 (hereafter ‘SIMOBS’) uses daily 1-km precipitation from CEH-GEAR (Tanguy et al. 2016) divided equally over each model time-step in a day; monthly 40-km short grass PE from MORECS (Hough and Jones 1997) divided equally over each model time-step in a month and copied down to the 1-km grid; and daily 1-km min and max temperature (Met Office et al. 2019) interpolated through the day using a sine curve (Kay and Crooks 2014). The simulation was initialised using a states file saved from the end of a prior simulation using the same driving data (January 1970–November 1980).

Model outputs include gridded time-series of (i) monthly mean river flows and (ii) annual maxima of daily mean river flows (for water years, 1st October–30th September). Also, time-series of daily mean river flows are output for specific 1-km grid boxes corresponding to gauged catchments within the National River Flow Archive ([www.ceh.ac.uk/data/nrfa](http://www.ceh.ac.uk/data/nrfa)). Only data from non-tidal grid boxes with a catchment area of at least 50 km<sup>2</sup> are analysed (hereafter ‘river pixels’).

### 2.2 Climate change projections and their application

UKCP18 comprises a number of products, including UKCP18 Regional (Murphy et al. 2018) and UKCP18 Local (Kendon et al. 2021b), which respectively provide the RCM and CPM data applied here. The Regional projections comprise a 12-member perturbed parameter

ensemble (PPE) of the Hadley Centre ~12-km RCM (HadREM3-GA705), nested in an equivalent PPE of the Hadley Centre ~60-km GCM (HadGEM3-GC3.05). The Local projections comprise a 12-member ensemble of the Hadley Centre ~2.2-km CPM (HadREM3-RA11M), nested in each RCM PPE member. The RCM/CPM ensemble members are numbered 01–15 excluding 02, 03, and 14 (there are no RCM/CPM equivalents for these three GCM PPE members; Murphy et al. 2018 Sect. 4.3). Member 01 uses the standard GCM/RCM parameterisation; the CPM parameters are not adjusted between members.

Both Regional and Local projections are for RCP8.5, a scenario of relatively high greenhouse gas emissions (Riahi et al. 2011). While the Regional projections cover December 1980–November 2080, the Local projections only cover three 20-year sub-periods; December 1980–November 2000, December 2020–November 2040 and December 2060–November 2080 (meaning that a WMO-recommended 30-year standard reference period, e.g. 1981–2010, cannot be used here). As well as the RCM and CPM data being available on their native ~12-km and ~2.2-km rotated lat-lon grids, the data are also available re-projected to grids aligned with the GB national grid, at resolutions of 12 km and 5 km respectively (Met Office Hadley Centre 2018, 2019). The re-projected 12-km RCM and 5-km CPM daily precipitation and min and max temperature are used here.

The re-projected RCM and CPM daily precipitation data are bias-corrected using monthly factors derived by comparing baseline data against CEH-GEAR data (as Kay 2021), down-scaled to 1 km using information from observed patterns of standard average annual rainfall (Bell et al. 2007), and temporally down-scaled as for observed rainfall (Sect. 2.1). No bias correction is applied to RCM or CPM temperature data (Kay 2021), but these are down-scaled to 1 km using elevation data and a lapse rate (Bell et al. 2016), and temporally down-scaled as for observed temperature (Sect. 2.1). Note that bias correction of climate model data is not straightforward (Ehret et al. 2012; Maraun et al. 2017), and deficiencies in observation networks (especially in areas of complex topography) could mean that CPM simulation skill exceeds the skill of gridded observations in some areas (Lucas-Picher et al. 2021).

PE for short grass is not available directly from the climate models and so is estimated from other climate variables (Kay 2021). Here, as in Kay et al. (2015), the RCM PE is used for the equivalent CPM runs, to simplify the application and because not all of the variables required to calculate PE are yet available for the CPM. Rudd and Kay (2016) showed good correspondence between PE derived from an RCM and the nested CPM. The RCM PE are spatially and temporally down-scaled as for observed PE (Sect. 2.1).

The RCM and CPM ensemble data are used to drive the G2G, using the full period for the RCM (December 1980–November 2080) but only the baseline (December 1980–November 2000) and far-future (December 2060–November 2080) time-slices for the CPM. The states file used to initialise SIMOBS (Sect. 2.1) is also used to initialise each RCM-driven simulation (hereafter ‘SIMRCM’) and each baseline CPM-driven simulation (hereafter ‘SIMCPM’). For the far-future CPM simulations, each ensemble member is initialised using a states file saved from the end of a 5-year prior run (December 2055–November 2060) of the equivalent RCM ensemble member (initialised using a states file from the end of the prior time-slice).

## 2.3 Analysis of simulated flows

### 2.3.1 Baseline performance assessment

The performance assessment compares flow statistics rather than day-to-day flow time-series, because the development of weather features (e.g. storms) in the RCM/CPM

baseline will not follow that of the observed weather. Thus, flow duration curves and flood frequency curves are derived from the simulated daily mean flows for 1-km grid cells corresponding to the locations of flow gauging stations (Sect. 2.1), and compared against those derived from the available gauged daily flow record. This is done for SIMOBS and each baseline SIMRCM and SIMCPM ensemble member (with and without bias correction). The comparison uses benchmark catchments (Harrigan et al. 2018), only including those with an area of at least 50 km<sup>2</sup> and with less than 20% missing data in the baseline (as Kay 2021)—94 catchments. Of these, the majority (71) have no missing data in the baseline. The presence of missing data could thus affect the assessment for 23 catchments, particularly for more extreme peak flows (which are more difficult to gauge) or if concentrated in a particular season for example.

Three measures are derived from the flow duration curve: low flow volume (percentage bias in the 70th–95th quantiles; *lfv\_70-95*), median flow (percentage bias in the 50th quantile; *mdf*), and high flow volume (percentage bias in the 5th–30th quantiles; *hfv\_5-30*) (as Kay 2021). These three measures symmetrically cover the flow duration curve, but exclude the extremes as greater uncertainty can be expected in extreme quantiles of gauged flows. An additional measure is derived from the flood frequency curve; the average percentage bias in 2-, 5- and 10-year return period peak flows (*ffr*; as Kay et al. 2015). The flood frequency curve is derived by fitting a generalised logistic distribution to sets of water-year annual maximum (AM) flows (use of water-years means there are 19 AM in each 20-year time-slice). All four measures are calculated on the square root of flows, so there is less emphasis on bias in very high flows. Better performance is indicated by values closer to zero.

### 2.3.2 Future changes in precipitation

To provide context for the simulated future changes in flows (Sect. 2.3.3), the changes in RCM and CPM seasonal and extreme precipitation are first calculated and compared across GB. For each RCM and CPM ensemble member and each land cell over mainland GB (i.e. excluding sea cells and data covering Ireland, France, Isle of Man and Orkney/Shetland), the changes in seasonal mean bias-corrected precipitation are calculated between the baseline and far-future time-slices, for the standard seasons (winter: December–February, spring: March–May, summer: June–August, autumn: September–November). Similarly, the baseline to far-future changes in extreme precipitation are calculated for each RCM and CPM ensemble member and each land cell over mainland GB, where ‘extreme’ is defined as daily rainfall exceeding the 90th or 99th percentile of the baseline daily rainfall in each cell. In each case, the GB-median of the grid-cell changes is then calculated and plotted.

### 2.3.3 Future changes in flows

To assess whether the RCM and CPM show different impacts on river flows, changes in SIMRCM and SIMCPM seasonal mean flows and peak flows are calculated from the baseline to the far-future time-slice. The gridded monthly mean flow time-series are used to derive seasonal mean flows for the standard seasons (as Kay 2021). The gridded AM flow time-series are used to derive flood frequency curves, and changes in 2- and 10-year return period peak flows are investigated.

### 3 Results

#### 3.1 Baseline performance assessment

The analysis of baseline performance shows that, without bias correction, SIMCPM generally performs better than SIMRCM; box plots show median performance values (across the ensemble and the 94 catchments) are closer to zero for SIMCPM than SIMRCM for all measures except flood frequency, for which there is little difference (Fig. 1). Similarly, scatter plots of the SIMCPM vs SIMRCM ensemble median performance values, for each of the 94 catchments, show lower-magnitude SIMCPM values for most catchments, for all measures except flood frequency (Fig. 2 left). Precipitation bias correction makes SIMRCM and SIMCPM perform more similarly to each other, with correlation coefficients of 0.867–0.979 for the four measures without bias correction but 0.977–0.996 with bias correction (Fig. 2). With bias correction, SIMRCM and SIMCPM also perform more similarly to SIMOBS (Fig. 1), although SIMOBS tends to underestimate low flow volume and flood peaks. Errors in low flow volume are accentuated by use of percentages, as a small absolute difference in a low value can be a large percentage difference.

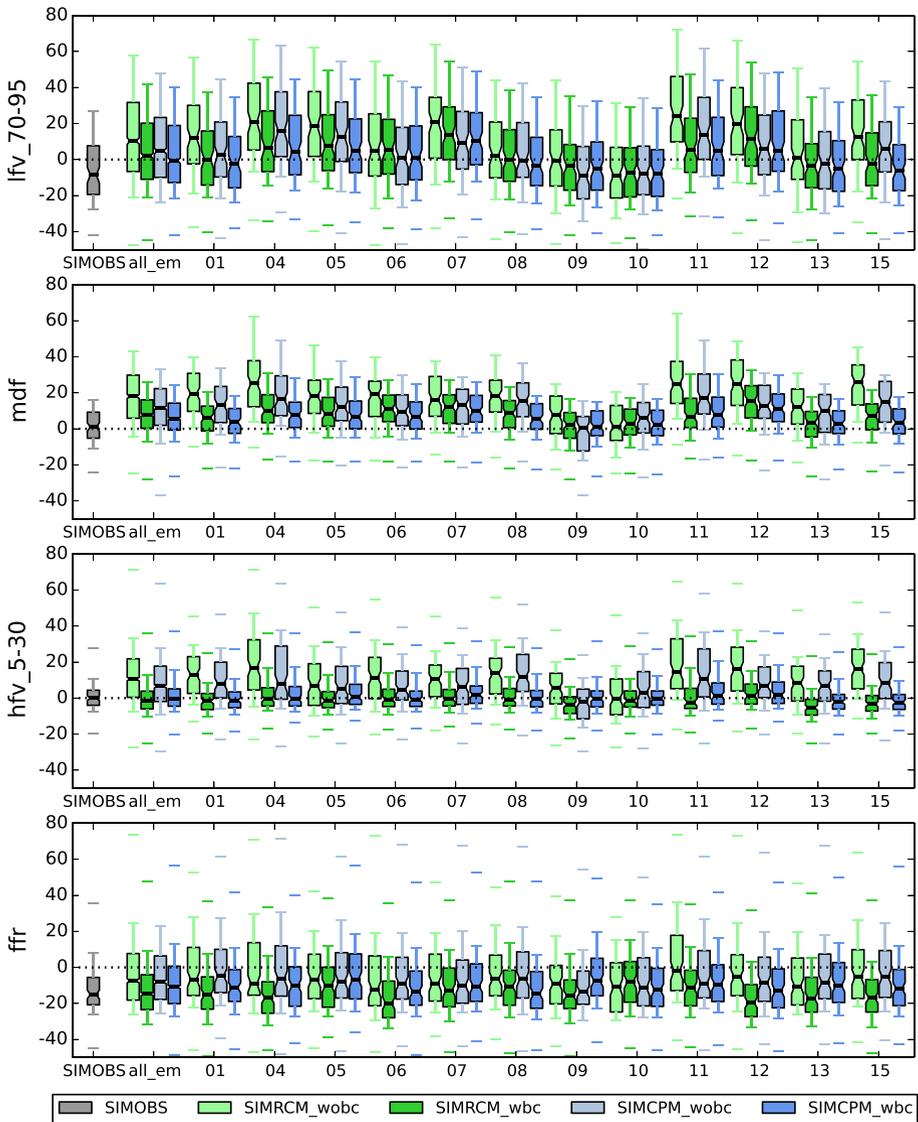
Maps of the performance measures for the 94 catchments, for SIMOBS and as the ensemble median for SIMRCM and SIMCPM (with and without bias correction), illustrate the spatial variation in performance (Supp. Fig. 1). Spatial patterns of performance are generally similar for SIMRCM and SIMCPM, and with bias correction these patterns are similar to those for SIMOBS, as would be expected. In particular, the low flow volume is more likely to be under-estimated in north/west England, Wales and eastern Scotland, while flood peaks are more likely to be under-estimated in Scotland and southern England/Wales.

#### 3.2 Future changes in precipitation

Looking at the GB-median of grid-based precipitation changes, both the RCM and CPM give increases in winter precipitation and extreme precipitation and decreases in summer precipitation for all ensemble members (Fig. 3). There is less consistency between ensemble members in terms of the sign of the precipitation change for spring and autumn, for both the RCM and CPM (Fig. 3).

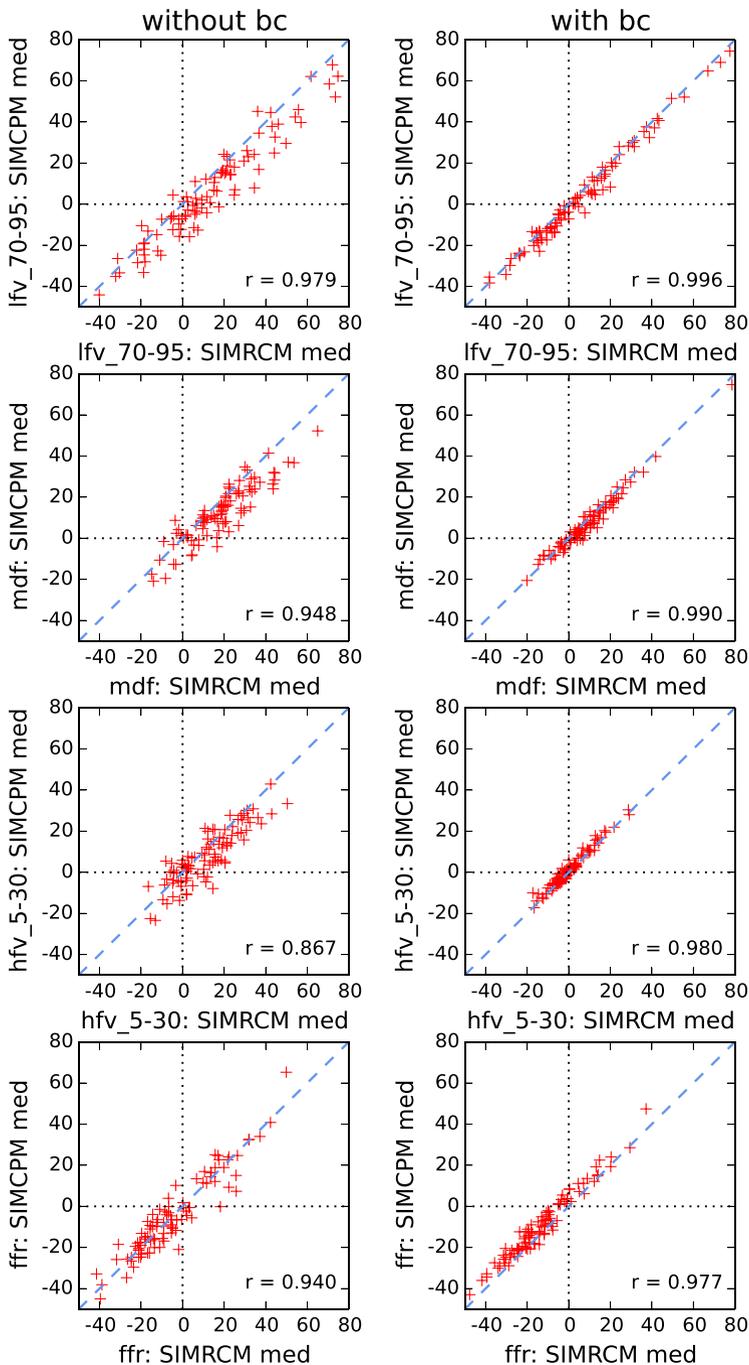
Comparing the RCM and CPM GB-median precipitation changes, the CPM generally gives a higher ensemble mean change than the RCM, with differences in winter and autumn of about +9–10% and in spring of about +4%. Differences between the RCM and CPM precipitation changes are much smaller for summer mean precipitation (about –2%) and for extreme precipitation (+2% or less) (Fig. 3).

The CPM ensemble members are not in the same order as the RCM members for any of the precipitation measures (Fig. 3). However, the member with the largest (smallest) change for the RCM is also the largest (smallest) for the CPM, or at least close to it (Fig. 3). The member that gives the largest or smallest difference between RCM and CPM precipitation changes is often not the same for the different precipitation measures (Fig. 3).



**Fig. 1** Boxplots summarising the four performance measures — percentage bias in low flow volume (*lfv\_70-95*), median flow (*mdf*), high flow volume (*hfv\_5-30*) and flood frequency (*ffr*) — across 94 gauged catchments, for SIMOBS, the SIMRCM and SIMCPM ensembles pooled together ('all\_em'), and each SIMRCM and SIMCPM ensemble member separately (numbers along the x-axis). The SIMRCM and SIMCPM results are shown without and with bias correction ('wobc' and 'wbc'). Each box shows the 25th–75th percentile range, with the line showing the 50th percentile and the whiskers the 10th–90th percentiles. Lines outside the box show the overall min and max (if within the plotted range)

More detail on RCM vs CPM precipitation changes is provided by Kendon et al. (2021b), in particular maps of changes in winter and summer mean precipitation (Kendon et al. 2021b Fig. 4.2.3–4.2.4) and changes in winter and summer wet day frequency, wet day intensity and heavy daily events (Kendon et al. 2021b Fig. 4.3.3–4.3.8).



**Fig. 2** Scatter plots comparing the four performance measures — percentage bias in low flow volume (*ifv\_70-95*), median flow (*mdf*), high flow volume (*hfv\_5-30*), and flood frequency (*ffr*) — for 94 gauged catchments, as the median value across the SIMRCM and SIMCPM ensemble members without and with bias correction ('bc'). The Pearson correlation coefficient  $r$  is given to the bottom right of each plot

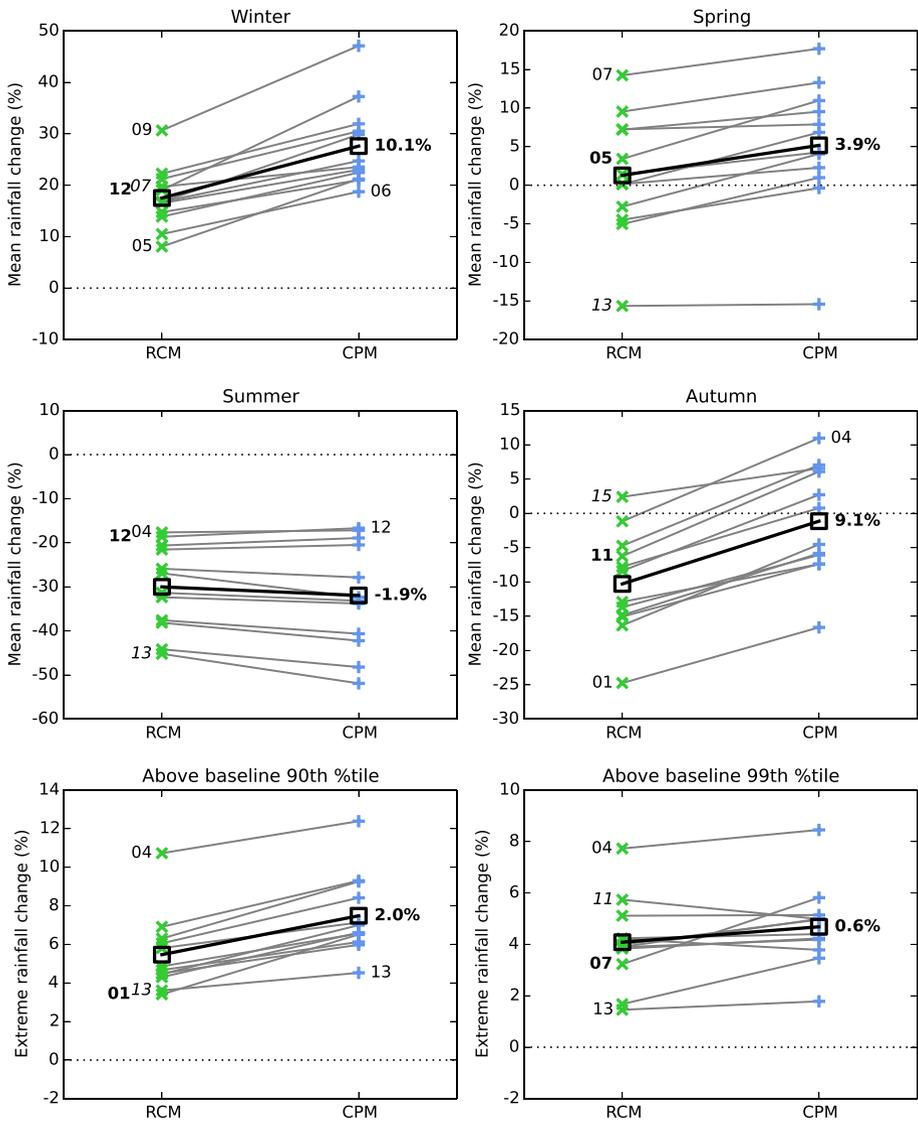
### 3.3 Future changes in flows

Comparing the GB-median of grid-based flow changes, SIMCPM gives a higher ensemble mean change than SIMRCM, with differences of about +13–14% for winter and autumn mean flows and 2- and 10-year return period peak flows, about +8% for spring mean flows, but only about +3% for summer mean flows (Fig. 4). For each flow measure except summer mean flows, the GB-median flow change from SIMCPM is greater than that from SIMRCM for all 12 ensemble members (i.e. the line connecting them has positive slope). For summer mean flows, all SIMRCM and SIMCPM members give decreases (ensemble mean ~ -50%) but two SIMCPM members (06, 13) give slightly larger decreases than their SIMRCM equivalents (i.e. the line connecting them has negative slope; Fig. 4). These members also give the greatest magnitude decreases in summer mean flows, which leads to the SIMCPM ensemble spread being clearly greater than that for SIMRCM for summer mean flow changes. The ensemble spread from SIMCPM is also greater than that for SIMRCM for the other flow measures.

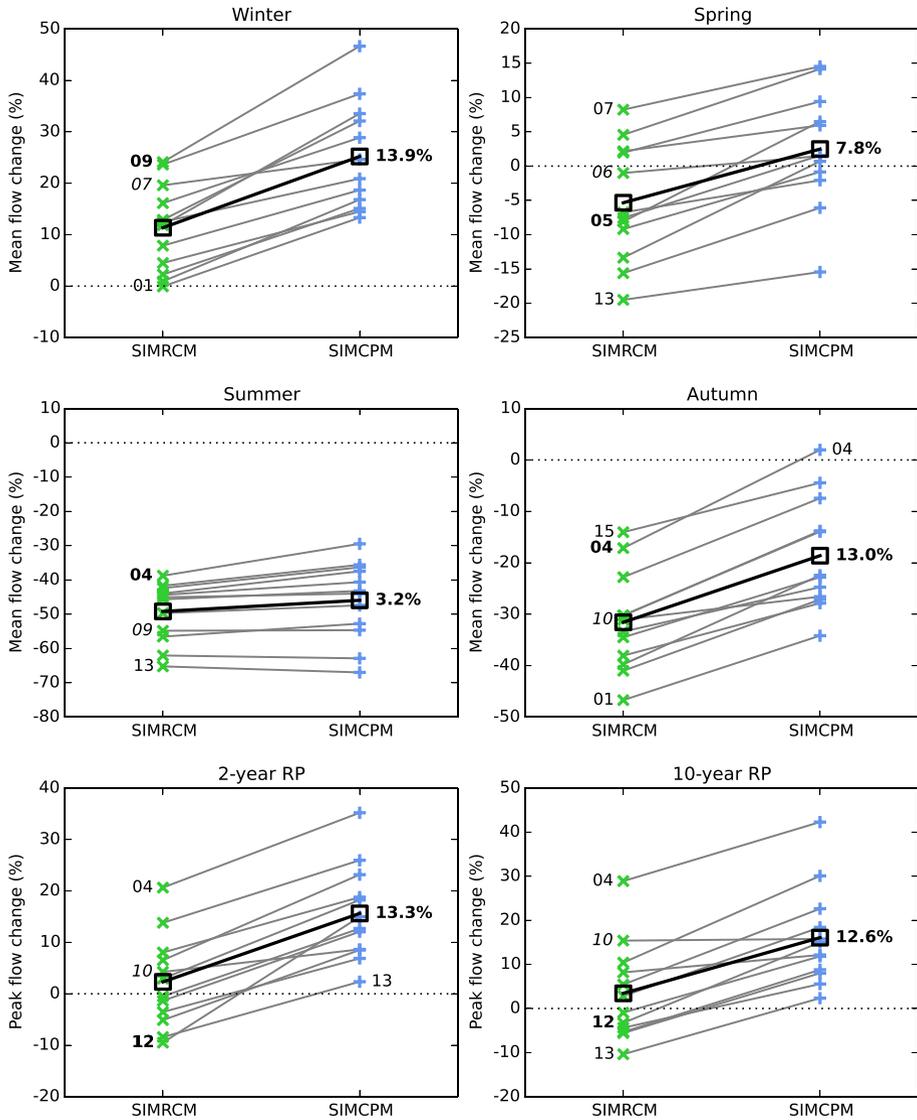
The SIMCPM ensemble members are not in the same order as SIMRCM for any of the flow measures (Fig. 4). However, the member with the largest (smallest) change for SIMRCM is also the largest (smallest) for SIMCPM, except for autumn mean flows (2-year return period peak flows). The member that gives the largest or smallest difference between SIMRCM and SIMCPM flow changes is also not generally the same for the different flow measures, apart from the two peak flow return periods (Fig. 4). The member that gives the largest difference in peak flow changes (12) also gives the near-largest difference in winter flow changes (not shown), while the member that gives the smallest difference in peak flow changes (10) also gives the smallest difference in autumn flow changes.

While Fig. 4 compares the GB-median flow changes for each ensemble member, Fig. 5 compares the distribution of flow changes for river pixels across GB, pooling the ensemble members. This illustrates that the 25th, 50th and 75th percentile changes from SIMCPM are greater than those from SIMRCM for all flow measures. The same is true for the min/max changes, except for the min in summer and autumn and the max for 10-year return period peak flows. The distributions for summer flows show that, although the majority of river pixels show decreases in flows, a small number show increases for some ensemble members. Plots of the distribution of flow changes for individual ensemble members show that, while there is a lot of overlap between members, there are also clear differences (Supp. Fig.2 and 3).

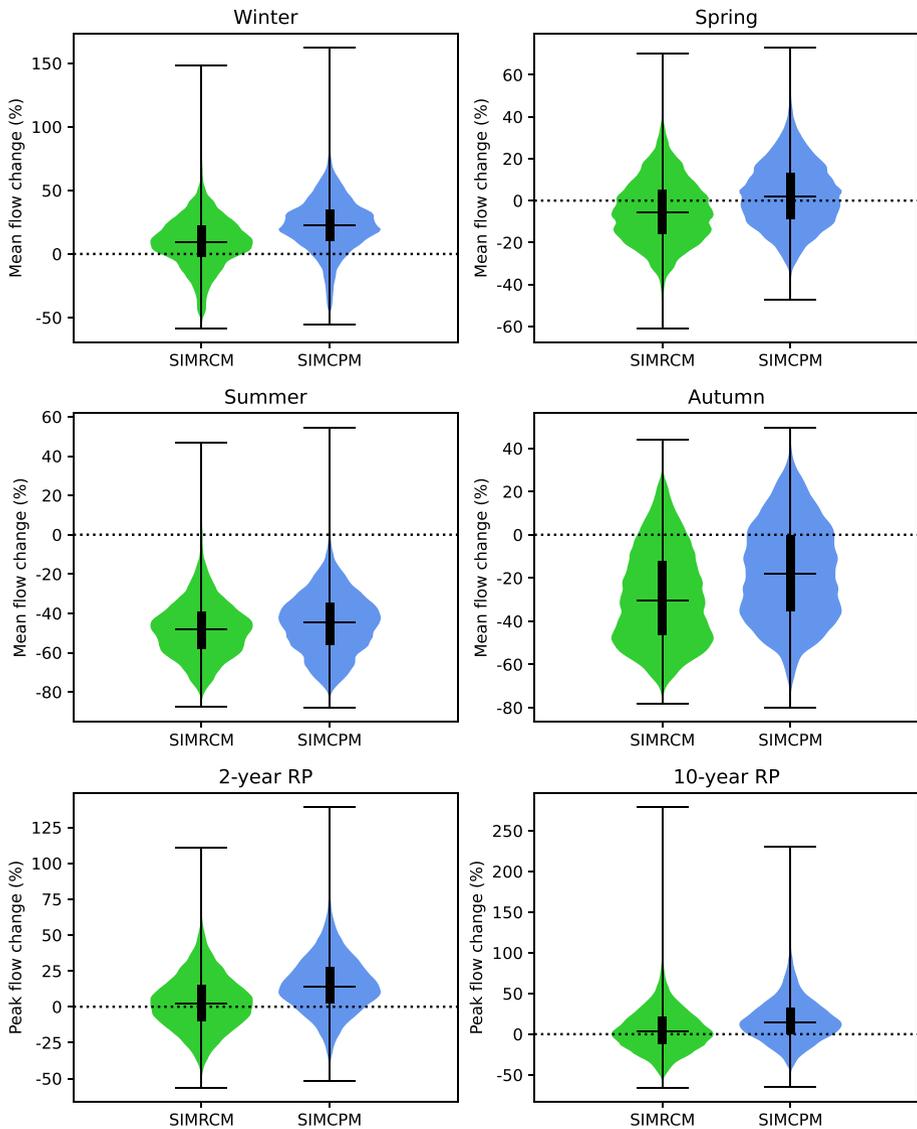
Further, the hexbin plots in Fig. 6 present pixel-based comparisons of SIMRCM and SIMCPM flow changes (for each river pixel across GB, again pooling the ensemble members). These show that, for most river pixels and ensemble members, SIMCPM changes are greater than SIMRCM changes. But for all flow measures, there are pixels where SIMCPM changes are lower than SIMRCM changes, particularly for spring and summer mean flows. Maps of the difference in SIMCPM and SIMRCM ensemble median flow changes show no clear spatial patterns (Fig. 7), although they do show the generally low difference everywhere in summer (GB mean 3.1%), the higher differences in autumn (GB mean 11.3%) and winter (GB mean 13.3%), and the particularly high differences in some locations for 2- and 10-year return period peak flows (GB max 39.8% and 48.0% respectively).



**Fig. 3** The median change in seasonal mean precipitation (top two rows) and extreme precipitation (bottom row) for land cells across GB, for each RCM and CPM ensemble member (green crosses and blue plus signs respectively). Lines join the equivalent ensemble members. The RCM members giving the largest or smallest precipitation changes are labelled, with the largest/smallest CPM members labelled where different. The members giving the largest (smallest) magnitude difference (CPM – RCM) are in bold (italics). Also shown is the ensemble mean in each case (black square and line), labelled with the value of CPM – RCM (right)



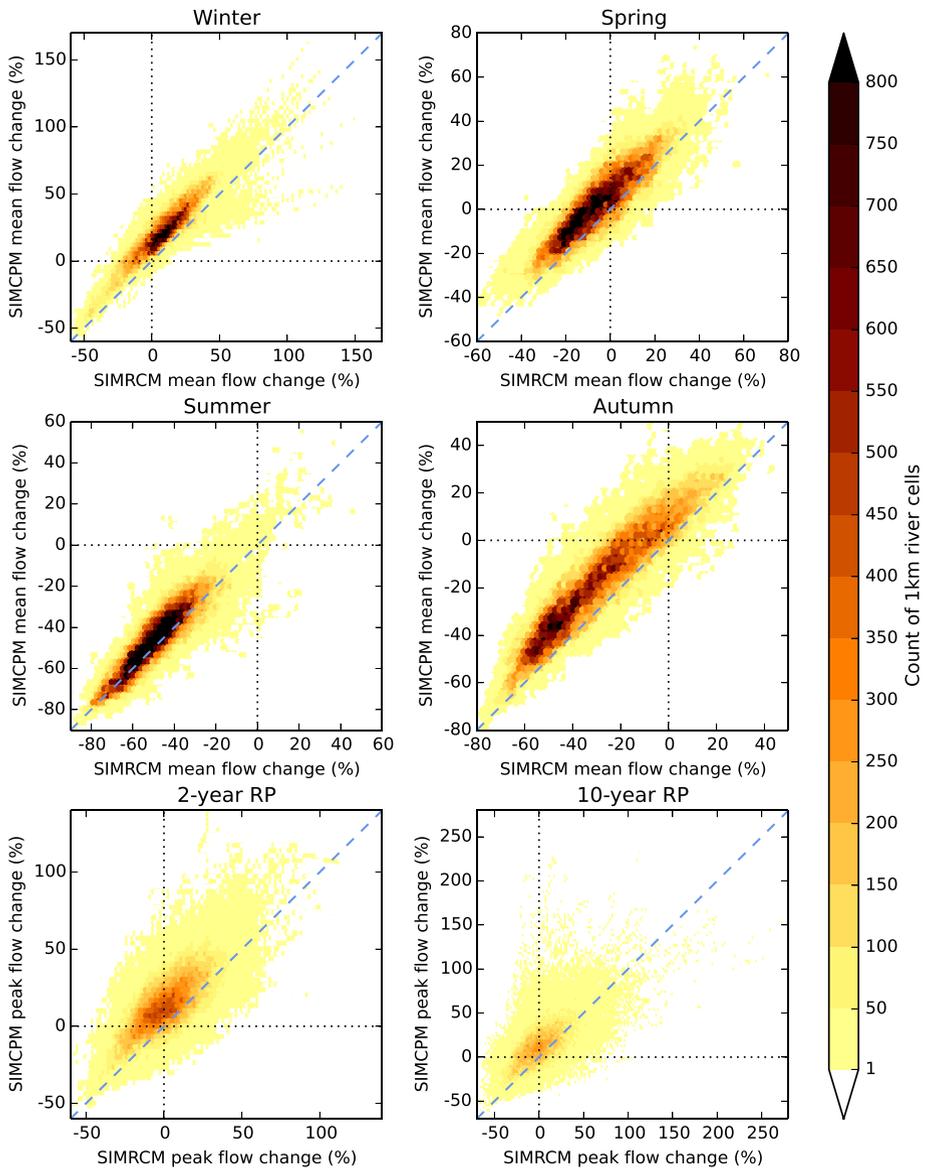
**Fig. 4** The median change in seasonal mean flows (top two rows) and 2- and 10-year return period peak flows (bottom row) for river pixels across GB, for each SIMRCM and SIMCPM ensemble member (green crosses and blue plus signs respectively). Lines join the equivalent ensemble members. The SIMRCM members giving the largest or smallest flow changes are labelled, with the largest/smallest SIMCPM – SIMRCM members giving the largest (smallest) magnitude difference (SIMCPM – SIMRCM) are in bold (italics). Also shown is the ensemble mean in each case (black square and line), labelled with the value of SIMCPM – SIMRCM (right)



**Fig. 5** Violin plots showing the distribution of changes in seasonal mean flows (top two rows) and 2- and 10-year return period peak flows (bottom row) for river pixels across GB, for the pooled SIMRCM ensemble (green) and SIMCPM ensemble (blue). In each case, the horizontal lines show the min, median and max changes, and the black box shows the 25th–75th percentile range

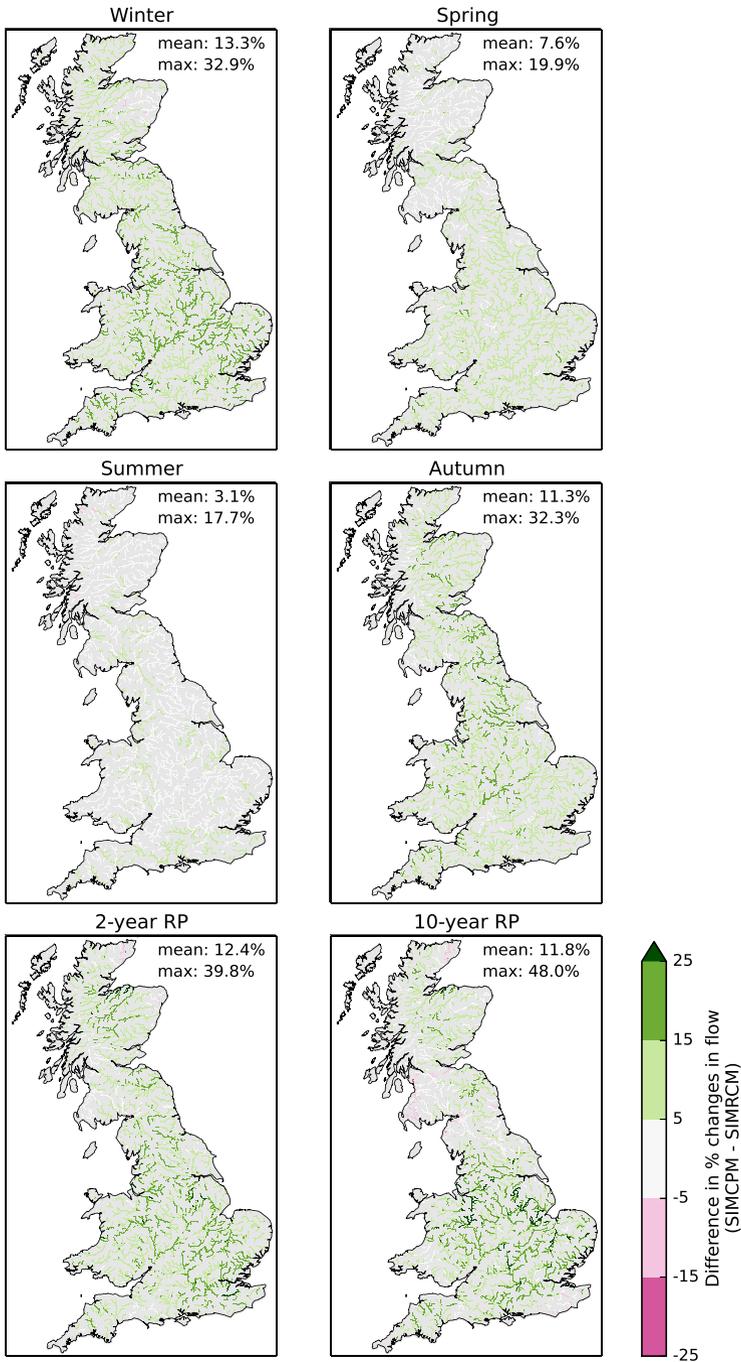
## 4 Discussion

The baseline performance assessment (Figs. 1 and 2) shows that, in contrast to Kay et al. (2015), SIMCPM generally performs better than SIMRCM (before bias correction). This is potentially due to the aforementioned CPM model physics changes (Fosser et al. 2020). Direct comparisons with the performance assessment presented in the previous work are



**Fig. 6** Heat maps of scatter plots comparing SIMCPM versus SIMRCM changes in seasonal mean flows (top two rows) and 2- and 10-year return period peak flows (bottom row) for river pixels across GB, for all ensemble members

not possible due to differences in methodology, including the hydrological model, catchments and time-periods used, plus Kay et al. (2015) used hourly precipitation from re-analysis-driven runs, in contrast to use here of daily precipitation from GCM-driven runs. The potential future changes in peak flows simulated here are broadly consistent with Kay et al.



**Fig. 7** Maps showing the difference between the ensemble median flow change from SIMCPM and SIM-RCM, for seasonal mean flows (top two rows) and 2- and 10-year return period peak flows (bottom row). The GB mean and max values are shown to the top right of each map

(2015), which also showed greater increases from the CPM than the RCM (Kay et al. 2015 did not analyse seasonal mean flows, only annual and seasonal peak flows).

The SIMCPM ensemble members almost always give greater increases in the median flow change across GB than their equivalent SIMRCM ensemble members, for seasonal mean flows in each season, and for 2- and 10-year return period peak flows (Fig. 4). But there is not complete consistency as the SIMCPM and SIMRCM members are not in the same order for any flow measure. For all flow measures, the SIMCPM ensemble spread is greater than that for SIMRCM, which is consistent with the CPM ensemble spread for seasonal precipitation changes being greater than that for the RCM in every season (Fig. 3).

The similar decreases in SIMRCM and SIMCPM summer mean flows (Figs. 4 and 5) are consistent with projected decreases in summer mean precipitation, which are only slightly different between the CPM and RCM (Fig. 3). The greater increases in winter mean flows from SIMCPM than SIMRCM (Figs. 4 and 5) are consistent with projected increases in winter mean precipitation, which are generally larger in the CPM than the RCM (Fig. 3) and due to greater increases in CPM than RCM wet day frequency (Kendon et al. 2021b Fig. 4.3.3). The greater increases in peak flows from SIMCPM than SIMRCM (Figs. 4 and 5) are consistent with the increases in winter mean precipitation and the slightly greater increases in extreme daily events in the CPM than the RCM (Fig. 3). However, note that a direct relationship between changes in precipitation extremes and changes in floods should not automatically be expected; changes in antecedent soil moisture, storm extents and (in some locations) snow also contribute (Sharma et al. 2018).

The potentially greater enhancement of flow seasonality, and greater increases in peak flows, suggested by the CPM compared to the RCM present a dilemma for adaptation planning, as decisions must be made on how to allow for differences in impacts between products. Orr et al. (2021) raise the difficult question of whether differences between products are ‘added-value’ or ‘model bias’. Similarly, Kendon et al. (2021a) ask what the presence of climate model baseline biases means for their future simulations, and highlight the need for better understanding of which climate change signals can be considered robust from coarser models and which need higher resolution modelling. A similar consideration is needed for hydrological modelling; which impacts, in what types of catchment, need higher-resolution driving data.

It is not just the higher spatial resolution of CPM data that could be important, but their provision of sub-daily precipitation, the representation of which is generally improved in the CPM compared to the RCM (Kendon et al. 2012). The analyses here were limited to catchments with an area greater than 50 km<sup>2</sup>, due to use of daily inputs. Orr et al. (2021) suggest use of CPM data for future flood risk in smaller/flashier catchments, where both the increased spatial and temporal resolution could be important. An analysis of sub-daily rainfall from the UKCP18 CPMs showed that, as well as heavy summer rainfall events becoming more intense in future, they could also move faster but cover a larger area (Chen et al. 2021). How such changes balance each other could be important for flows in some catchments, and for surface water flooding (Rudd et al. 2020).

A further difficulty for decision-makers is that the UKCP18 Regional and Local projections are based on just the Hadley Centre GCM, so uncertainty from GCM structure is not represented, and neither is real uncertainty from the CPM as its parameters are not perturbed (although GCM/RCM PPEs are used). In addition, only high emissions (RCP8.5) are used. Kay et al. (2021) showed a clear distinction between extreme flow changes derived from the Hadley GCM and other CMIP5 GCMs, and Arnell et al. (2021) showed more consistent flood increases from CMIP5 GCMs than the Hadley GCM. Although the

high emissions scenario is meaningful for many purposes (Orr et al. 2021), the global aim is to keep emissions lower so impacts should be lower (Arnell et al. 2021).

Only one hydrological model has been applied, and although climate models are generally considered the main source of uncertainty for hydrological impacts (e.g. Hattermann et al. 2018; Thober et al. 2018; Vetter et al. 2017), hydrological model uncertainty can still be significant. Dankers and Kundzewicz (2020) suggest that the main sources of hydrological bias are related to evaporation and snow processes. River flows in most British catchments are rainfall-dominated, but snowmelt can be significant for some upland catchments (Kay 2016); a snow module is applied here to account for snow processes, albeit in a relatively simple way. Appropriate representation of PE is important, particularly under climate change (Kay et al. 2013). In contrast to many hydrological impact studies (Dankers & Kundzewicz 2020), here the future PE includes the effect of stomatal closure under higher concentrations of atmospheric carbon dioxide (Robinson et al. 2021). The use of RCM PE for both SIMRCM and SIMCPM means that the differences in impacts are essentially due to precipitation differences, possibly with some effect from temperature differences in some catchments (although CPM and RCM winter temperature projections are broadly similar; Kendon et al. 2021b Fig. 5.1).

For peak flows, the method used for deriving flood frequency could be an additional source of uncertainty (Tabari 2021; Meresa et al. 2021), and peak flow changes derived from sub-daily flows may differ to those from daily flows (Kim et al. 2018). The peak flow analysis here was limited to catchments of at least 50 km<sup>2</sup> and at most a 10-year return period, using 19 annual maxima in each time-slice, to limit the uncertainty. Also, due to natural climate variability, the choice of baseline period can have a significant effect on derived flow changes for future periods (Liersch et al. 2020). Due to CPM data availability, the analysis here is restricted to a 20-year baseline of 1981–2000; a WMO-recommended 30-year standard reference period (e.g. 1981–2010) could not be used.

## 5 Conclusions

The UKPC18 Local projections provide very high-resolution climate data for the UK, produced by a convection-permitting model (CPM) ensemble for baseline and future periods. These data have been applied alongside the UKCP18 Regional projections, produced by the regional climate model (RCM) perturbed parameter ensemble within which the CPM ensemble is nested, to drive a grid-based hydrological model for Great Britain. The simulated flows have been analysed to investigate baseline performance and differences in projected future impacts on river flows.

The baseline performance analysis shows that the CPM generally performs better than the RCM, although precipitation bias correction makes both the RCM and CPM perform more similarly to use of observation-based driving data. The analysis of changes in flows between the baseline and far-future time-slices shows that the CPM almost always gives higher flow changes than the RCM, for mean flow in all four seasons and for 2- and 10-year return period peak flows. If reliable, these differences in flow projections suggest that adaptation planning for high flows based on use of regional data may be insufficient, although planning for low flows may be slightly over-cautious. But the availability of CPM data for only one RCM/GCM is a limitation for adaptation planning, as is the use here of only one hydrological model and one PE formulation, as the uncertainty range is under-sampled.

Knutti (2019) suggest that one way for the gap between knowledge (about the potential future impacts of climate change) and action (adaptation to reduce the effect of those impacts) can be closed is the provision of “more local climate information that is more relevant for impacts, adaptation, and risk management”. However, delivering this with CPMs is currently not straightforward; Knutti (2019) acknowledge that “the technical challenges of providing sufficient computing power with new computing architectures and processing and storing massive amounts of data are immense”. Possible ways to address issues include using targeted CPM downscaling or ‘storyline’ approaches, and the development of statistical methods or emulators to more cheaply combine limited CPM simulations with coarser-resolution projections from a wider range of GCMs/RCMs (Lucas-Picher et al. 2021; Kendon et al. 2021a). However, the potential effect of such methods on the ability to perform impact simulations needs consideration.

Uncertainty in the assessment of the future impacts of climate change comes from a wide range of sources, some of which may be reducible (e.g. via improvements in physical process understanding), but uncertainty from newer sets of climate and impact projections can still be larger than from previous generations (Kundzewicz et al. 2018). The key challenge for adaptation action is to “robustly quantify uncertainties in all aspects of the science and embrace the concepts of risk management and resilience” (Knutti 2019).

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**Data availability** The SIMRCM and SIMCPM data are available from the author upon reasonable request.

## Declarations

**Conflict of interest** The authors declare no competing interests.

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