Can regional climate models reproduce the historic magnitude and frequency of severe UK extreme rainfall events, and how will this change under global warming?

H.J. Fowler, S. Blenkinsop, A.P. Smith, M. Ekstrom and C.G. Kilsby

Introduction

Recent extreme weather events and record wet spells, such as the autumn and winter UK floods of 2000/01 (Marsh, 2001) and summer 2002 European (Elbe) flooding, have focused attention on the possible impacts of climate change on our society, and created public concern that such events are increasing, possibly due to global warming. In 2000/01, UK flood events produced insurance claims totalling £500M (RMS, 2000). Flooding, and managing floods, presently costs the UK £2.2 billion annually and costs may rise to £27 billion by the 2080s under the most severe emissions scenario (OST, 2004).

Evidence from climate models (e.g. Frei et al., 1998, 2006; Ekstrom et al., 2005) suggests that warming may lead to an intensification of the hydrological cycle and increases in mean and heavy rainfall. Indeed, significant increases in extreme rainfall events have been seen over the last decade in many regions of Europe (e.g. Fowler and Kilsby, 2003a,b; Frei and Schar, 2001).

The ability of regional climate models (RCMs) to reproduce extreme climate statistics has been assessed in a few studies concentrating on rainfall. For example, the HadRM3H RCM was found to represent extreme rainfall events with return periods of up to 50 years well for most of the UK (Fowler et al., 2005). The main deficiencies in the model’s representation of extremes were found to be related to the treatment of orographic rainfall processes; consequently extremes in north Scotland were over-estimated, with the converse happening in eastern rain-shadow regions. Such assessments of model performance are crucial if they are to be applied with confidence to the prediction of future extremes under enhanced greenhouse conditions (e.g. Ekström et al., 2005). However, as most uncertainty in future climate is derived from the choice of climate model and emissions scenario (Déqué et al., 2006), a better understanding of the range of possible future change may be derived by comparing results from a number of climate models, as even models sharing similar parameterisation schemes may produce considerably different rainfall statistics (Frei et al., 2003).

Most studies of future change in extreme rainfall to date have examined the results from only one regional or global climate model. However, now that simulations from different regional climate models and different global–regional model combinations are available for future climate over Europe from projects like PRUDENCE (Christensen et al., 2006), it is important that the uncertainty in estimates of future change in extremes is assessed. Frei et al. (2006) evaluated the performance of dynamical downscaling of daily precipitation extremes for the European Alps using six RCMs driven by a single AGCM HadAM3H, to derive a range of estimates for future change in extremes. The models showed some skill in reproducing the 5-year return value but the range of estimates of future change, particularly in summer months, suggests that the choice of RCM introduces additional uncertainty.

This study uses six state-of-the-art regional climate models (RCMs) from the PRUDENCE project to explore whether RCMs can reproduce the historic magnitude and frequency of UK severe extreme rainfall events during 1961–1990; then examining how their frequency, severity and timing may change under global warming. The analysis was performed using Regional Frequency Analysis, and annual maxima of 1-, 2-, 5-, 10- and 20-day rainfall totals. The Generalized Extreme Value (GEV) distribution was fitted using the method of L-moments to define extremes with given return periods. In this paper, we estimate the rainfall amounts associated with 10- and 50-year return periods for RCM control integrations, 1961–1990, and compare these to estimates using observations. We then examine RCM future integrations, 2071–2100, and compare these estimates with those for the control integrations, 1961–1990, to establish the likely pattern of change in extreme rainfall events over the UK resulting from global warming. We examine whether different RCM-driving-GCM combinations produce very different future changes for 2071–2100, under the SRES A2 emissions scenario and whether the GCM or RCM provides the greatest source of uncertainty. We then consider how we may combine estimates from different models to produce probabilistic estimates of future change in the risk of occurrence of extreme events, rather than simply providing a projected range of change.

Data and methods

A daily gridded observed 5 km precipitation dataset produced by the UK Meteorological Office (Perry and Hollis, 2005a, b) has been aggregated to the 50 km scale
by taking a daily average across the 5 km grid boxes contained in the 50 km grid cell for each day of 1961–1990. This has been used for direct comparison with the RCM data. This series will be referred to as UKMO.

Regional climate model data from the FP5 PRUDENCE project provides a series of high-resolution regional climate change scenarios for a large range of climatic variables for Europe for 2071–2100. Although it is infeasible to evaluate climate change impacts arising from every simulation made available by PRUDENCE, it is important to examine a range of models to evaluate the uncertainty of future predictions. Déqué (2006) indicated that for the European domain, individual RCMs provide a greater range of temperature change than the difference between GCMs and RCMs. Additionally, although RCMs provide an adequate representation of temperature across Europe, when comparisons are made between control climate integrations and observations, simulations of precipitation are inadequate. PRUDENCE provides advice on the selection of RCM experiments for impacts analysis. Here a selection has been made to examine the following uncertainty sources:

- Bounding GCM v. downscaled RCM
- Same bounding GCM/different RCMs
- Same RCM/different bounding GCMs

A list of models and their acronyms is provided in Table 1. Model simulations are available for control (1961–1990) and future (2071–2100) time-slices. Each model simulation was re-gridded onto a common 0.5° × 0.5° grid to allow direct comparison with the UKMO series.

Two methods are used to assess the performance of the six RCMs in the simulation of UK extreme rainfall and provide estimates of future change in extreme rainfall: regional frequency analysis (RFA) and individual grid box analysis (GBA). Both methods derive extreme value distributions of rainfall for 1-, 2-, 5- and 10-day annual maximum events, fitted using L-moments ( Hosking and Wallis, 1997). The RFA involves the regional pooling of annual maxima and allows a more reliable estimation of high return period rainfall events. The GBA provides additional information on the spatial distribution of extremes.

The RFA builds on the regionalisation of UK rainfall first developed by Wigley et al. (1984). This regionalisation identified five spatially coherent regions for England and Wales, three for Scotland and one for Northern Ireland. For each region, a standard regional frequency analysis (RFA) based on L-moments ( Hosking and Wallis, 1997) was used to generate ‘growth curves’ for the rainfall annual maxima (AM) data sets. This used the UKMO dataset, and the control and future scenarios from each RCM. The UK 50 km (0.5°) grid and the regions used in this study are shown in Figure 1.

A growth curve is a standardised extreme value plot of annual maxima. Here, we standardise by R Burnett (the median AM rainfall), following the method used in the Flood Estimation Handbook (IH, 1999). For each grid box, AM were standardised using the grid box R Burnett for that period. L-moment ratios derived from single grid box analyses within a region were then combined by regional averaging ( after Hosking and Wallis, 1997). A GEV distribution or ‘growth curve’ was then fitted for each region and aggregation level (1-, 2-, 5-, 10- and 20-days) for each dataset by matching the sample L-moments to the distribution L-moments. Using these growth curves, the event magnitude for different return periods were estimated for each dataset and region using the fitted growth factor, multiplied by the regional R Burnett. For the grid box analysis, the event magnitude at different return periods were estimated individually per grid box, based on the same L-moment approach as the RFA. This methodology is explained in more detail in Fowler and Kilsby (2003a).

In this paper we estimate the rainfall amounts associated with 10- and 50-year return periods for the RCM control integrations and compare these to observed

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**Table 1** Selection of PRUDENCE Regional Climate Models. The AquaTerra acronyms are adopted here to provide an easier understanding of the format of each model run. The first part of each acronym refers to the RCM and the second to the GCM data used to provide the boundary conditions. Scenario simulations have the further suffix _A2_.

<table>
<thead>
<tr>
<th>RCM</th>
<th>Driving data</th>
<th>PRUDENCE acronym</th>
<th>AquaTerra acronym</th>
</tr>
</thead>
<tbody>
<tr>
<td>Danish Meteorological Institute (DMI)</td>
<td>HIRHAM</td>
<td>HadAM3H A2</td>
<td>HC1</td>
</tr>
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<td></td>
<td></td>
<td>ECHAM4/OPYC A2</td>
<td>ecctrl</td>
</tr>
<tr>
<td>Swedish Meteorological and Hydrological Institute (SMHI)</td>
<td>RCAO</td>
<td>HadAM3H A2</td>
<td>HCTL</td>
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<td></td>
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<td>MPCTL</td>
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<td>Hadley Centre – UK Met Office</td>
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<td>HadAM3P A2</td>
<td>adeha</td>
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<tr>
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<td>Arpège</td>
<td>HadCM3 A2</td>
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estimates for the ‘common’ period 1961–1990, then calculating the difference between the RCM control and future, 2071–2100, to give estimates of future change in extremes.

**Results**

**Mean rainfall**

The RCMs broadly simulate the observed annual cycle of precipitation for the control period over the UK (Figure 2a). HIRHAM_E captures mean monthly precipitation most consistently but HAD_P significantly underestimates precipitation, particularly during summer and autumn. Model skill differs throughout the year and is most influenced by choice of RCM, except in autumn when precipitation tends to be greatest. Here, the driving GCM provides significant differences: RCMs driven by ECHAM4 over-estimate precipitation and those driven by Hadley GCMs under-estimate precipitation. This perhaps suggests a seasonal disparity in model ability to capture specific precipitation mechanisms. The proportion of dry days (PD, <1 mm), an indicator of how well models are able to reflect precipitation occurrence processes, is shown in Figure 2b and suggests that for the precipitation occurrence process, choice of GCM or RCM has a similar influence.

Figure 2a indicates that in winter the HIRHAM model is skillful in simulating mean precipitation across the UK. However, Figure 3 demonstrates that this hides important regional variations which compensate for each other. HIRHAM produces large underestimates over the north and west and overestimates over central and eastern England. RCAO produces similar spatial disparities and HAD_P significantly underestimates precipitation for most areas. If ARPEGE_C is considered, Figure 2a suggests that the model does not perform as well in simulating mean precipitation as other models. However, this is not because errors are large in relation to the other models but because errors are largely of the same sign. Indeed, the lack of a clear spatial pattern to the ARPEGE_C anomalies suggests that it may be better at representing the physical processes which produce the observed spatial pattern of rainfall than models which produce errors with a well-defined spatial structure. This raises important questions as to how the performance of climate models should be assessed: i.e. should the spatial distribution of model errors be used to assess model performance?

Under SRES A2 2071-2100, the RCMs project a peak precipitation increase in December and January, a small increase in spring, and decreases from June to September. Evidence for similar change to the seasonal distribution of UK precipitation has already been observed (Osborn and Hulme, 2002). There is no clear distinction between the choice of RCM and of the driving GCM in determining future change in mean precipitation across the UK. Changes in intensity are at least in part explained by changes in PD, with summer decreases in precipitation intensity coupled to increases in PD for all models.

In winter, Hadley-driven models project a gradient of increase in precipitation, largest over southern England and over northern Scotland (not shown). This would reduce the current northwest–southeast gradient in winter precipitation. A very different pattern of change is predicted by ECHAM-driven models. HIRHAM_E predicts a gradient of change that is the reverse of the Hadley-driven models, with the largest percentage increases over northern Scotland, whilst RCAO_E suggests a uniform pattern of large increases. Therefore, much uncertainty remains in the projection of future change in mean precipitation across the UK.

**Precipitation extremes**

Figure 4 shows the estimate of the 1-day, 10-year return period precipitation event for the UKMO dataset and each of the six RCMs for individual grid boxes (Figure 4a) and the regions (Figure 4b) for the control period, 1961–1990. At the 1-day aggregation level, all models underestimate extreme rainfall amounts at low and high return periods. This was noted by Fowler et al. (2005) for the HadRM3H model and is thought to be the result of the poor performance of the RCMs in resolving convective rainfall processes, since the 1-day AM may result from convective summer and autumn storms, particularly in southern regions of the UK. As precipitation is aggregated to the regional level, it can be seen that model performance improves due to an averaging effect (Figure 4b).

However, there is considerable variability in model performance over time and space. Figure 4a shows that the RCAO model in particular shows very little spatial variation in return period estimates for the 1-day, 10-year return period event, with a range across the UK from 27 to 45 mm, despite the observed range being from 36 to 99 mm. For longer duration events, the models provide better estimates. Figure 5 shows the estimate of the 10-day, 10-year return period precipitation event for the UKMO...
dataset and each of the six RCMs for individual grid boxes for the control period, 1961–1990. All models show a reduction in simulation error when compared to 1-day estimates, but the RCAO models still show a lack of spatial variability when compared to other RCMs. This improvement at longer durations may be due to the models’ ability to better resolve frontal precipitation processes that tend to produce rainfall over longer durations. Interestingly, despite the dry bias in mean precipitation across the UK simulated with the Had_P model, it produces the best simulations of extreme rainfall for the control period when compared with the UKMO estimates. This is a similar to results obtained for the HadRM3H model by Fowler et al. (2005).

Figure 6 shows the estimate of percentage future change in the 1-day and 20-day, 10-year return period event for the 2071–2100 SRES A2 scenario, taking the percentage change between the control and future scenarios. Model projections of future change in extreme rainfall vary considerably, with estimates ranging from −10 to +70% change in the 1-day 10-year return period event and from −10 to +50% change in the 20-day 10-year return period event, respectively, for UK regions. At the grid cell level (not shown), models predict changes of up
Figure 3  Observed and RCM simulated mean winter (DJF) daily precipitation for the period 1961-1990.

Figure 4  Estimate of 1-day, 10-year return period event magnitude (in mm) for (a) individual grid boxes (GBA), and (b) regions (RFA).
Figure 5  Estimate of 10-day, 10-year return period event magnitude (in mm) for individual grid boxes (GBA).

Figure 6  Percentage change in (a) 1-day, 10-year return period precipitation event, and (b) 20-day, 10-year return period precipitation event, for the SRES A2 2071-2100 scenario
to +120%. However, it can be seen that very few models predict decreases in any region, particularly for longer duration events. Consistently larger increases are predicted for northern and western regions of the UK by all models, excepting the Had_P model for North Scotland. Additionally, for longer duration extremes, models consistently project increases, with smaller increases for larger return period events. This suggests a change in the shape of the extreme rainfall distribution in future climates and will be investigated in further work.

Discussion and conclusions

A selection of six regional climate models from the set of PRUDENCE experiments have been used to assess the ability of each model to accurately reproduce observed climate statistics for the 1961–1990 control integration. All models reproduce the form of the annual cycle of precipitation when grid cells are averaged over the British Isles, with HIRHAM_5 performing best and Had_P notably underestimating precipitation totals throughout the year. However, the spatial distribution of model precipitation anomalies indicates that the models may have difficulty in capturing important physical processes that are responsible for precipitation. Future projections of change in mean precipitation indicate an increase during winter months with decreases during summer. However, during the summer in Scotland and northern England there is uncertainty as to the sign of change, with three models indicating small increases in precipitation.

In the simulation of extreme rainfall, there is considerable variability in model performance over time and space, but the Had_P model appears to perform the best for the control period in the UK. All models underestimate 1-day extreme rainfall but improve as rainfall is aggregated to longer durations. For the future period, 2071–2100, model projections of change in extreme rainfall vary considerably but few models predict decreases in any region. Consistently larger increases are predicted for northern and western regions and, for longer duration extremes, models consistently predict increases but these are larger for smaller return period events.

The choice of GCM and RCM seems very important in determining model accuracy in the simulation of precipitation extremes. For the control scenario, the RCM has an important influence on the spatial distribution of extremes and their magnitude, with the driving GCM providing little influence. However, for the future scenario, the driving GCM exerts a stronger influence, with ECHAM4-driven RCMs projecting increases in extreme precipitation of much greater magnitude than those from Hadley-driven GCMs. This is thought to result from the much greater increase in temperature over the UK projected by ECHAM4, on average 1.5°C more than corresponding RCMs driven by Hadley GCMs, with a resulting impact on the intensity of the hydrological cycle and thus precipitation extremes. However, in the future simulations, the RCM still exerts an influence over the spatial pattern of change in extreme precipitation.

An important further question is how can we use the estimates from different climate models to produce probabilities of future change that can be used in design, rather than simply a range of change? It is clear that, if models are to be quantitatively assessed and weighted for use in the production of probabilistic climate change scenarios, the choice of criteria on which to apply the weights is not a trivial one. This study of six RCM simulations suggests that it is impossible to designate a ‘best model’ as simulation skill varies for key statistics of precipitation, both temporally and spatially. Important questions must be asked as to how models should be assessed, as those models which well reproduce the observed mean statistics of regional climate can perform poorly when spatial biases are examined. Given that within-region differences are likely to be important when considering specific impacts of climate change, it may be more appropriate to assess how well models reflect spatial climate characteristics. The examination of mean precipitation indicates that large opposing errors in different regions are apparent in some models, indicating potential weaknesses in capturing important precipitation processes. If an impacts study is considering the regional effects of climate change, then such potential errors need to be considered. In this regard, climate models should be ‘fit for purpose’. For example, models which reproduce the spatial distribution of precipitation well may not be so useful for examining impacts associated with short-duration extremes if these are not so well represented. Clearly, any impacts study should therefore select a climate model carefully or preferably adopt a multi-model approach which will allow the assessment of uncertainty in future estimates of change through the generation of probabilistic scenarios.

In future work we will examine the potential to combine the results from the six RCMs to produce probabilistic estimates of change in extreme precipitation for different regions of the UK, and incorporate uncertainty estimates. Methods will also be developed to apply these probabilistic estimates in impact studies. In terms of future change, the RCMs indicate considerable uncertainty, with possible change in both directions. This represents a significant challenge, not just for management of change but for the research community in communicating the nature of this uncertainty to resource planners. It is clear that future strategy of an important strategic resource should not be based on the use of just one climate model and the generation of probabilistic scenarios of impacts of climate change offers considerable potential to achieve this.

Acknowledgments

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References


