Human influence on climate in the 2014 Southern England winter floods and their impacts

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A succession of storms reaching Southern England in the winter of 2013/2014 caused severe floods and £451 million insured losses. In a large ensemble of climate model simulations, we find that, as well as increasing the amount of moisture the atmosphere can hold, anthropogenic warming caused a small but significant increase in the number of January days with westerly flow, both of which increased extreme precipitation. Hydrological modelling indicates this increased extreme 30-day-average Thames river flows, and slightly increased daily peak flows, consistent with the understanding of the catchment's sensitivity to longer-duration precipitation and changes in the role of snowmelt. Consequently, flood risk mapping shows a small increase in properties in the Thames catchment potentially at risk of riverine flooding, with a substantial range of uncertainty, demonstrating the importance of explicit modelling of impacts and relatively subtle changes in weather-related risks when quantifying present-day effects of human influence on climate.

The winter of 2013/2014, and January in particular, saw above-average precipitation over England and Wales[1,2] and below-average sea level pressure (SLP) in the North Atlantic north and west of the British Isles (Fig. 1a-b). This persistent synoptic situation was associated with a near-continuous succession of low-pressure systems moving in from the Atlantic and across Southern England[1]. Like the very wet autumn of 2000 in England and Wales[3], this winter was characterized by an anomalous eastward extension of the jet stream (Fig. 2a). This persistent atmospheric circulation pattern resulted in extreme precipitation (Supplementary Fig. 1), flooding and storm surges in large parts of Southern England and Wales, with serious consequences for infrastructure and livelihoods[1]. 18,700 flood insurance claims were reported[4], leading to £451 million insured losses in Southern England. Although not unprecedented, this was a significant event; comparative UK insurance losses[5] in recent history include flooding in the summer of 2007, which cost £3 billion, the 2005 floods in Carlisle (£272 million) and Cumbrian floods in November 2009 (£174 million). Daily total precipitation, recorded since 1767 at the Radcliffe Observatory in Oxford (continuously since 1827), shows January 2014, as well as winter 2013/2014, precipitation set a record (Fig. 3a). Sustained high precipitation amounts during the whole winter led to this record, rather than a few very wet days, and none of the 5-day precipitation averages over the three winter months was a record (Fig. 3b). Similarly, while Thames´ daily peak river flows were not exceptional, the 30-day peak flow was the second highest since measurements began in 1883 (Supplementary Fig. 10). Whether anthropogenic climate change contributed to this event was much discussed at the time, with the British Prime Minister David Cameron telling Parliament “I very much suspect that it is”[6]. Although in a chaotic system a single extreme event cannot be attributed to changes in boundary conditions[7], the change in risk of a class of extremes in the current climate relative to a climate unaltered by anthropogenic greenhouse gas (GHG) emissions can be estimated[8]. This study uses a range of models and observations to estimate anthropogenic influence on the risk of experiencing such atmospheric flow and precipitation, separating thermodynamic and dynamic factors. To estimate the impacts of climate change, we use a hydrological model to calculate the anthropogenic changes in risk in peak flows of the river Thames. Finally, with detailed flood maps of the Thames basin we estimate the number of properties put at additional risk of flooding by anthropogenic GHG emissions.

1. Experimental setup and model evaluation

We use the citizen-science project "weather@home"[9] to produce an ensemble of 134,354 simulations of possible weather under current climate and under counterfactual conditions as might have been without human influence on atmospheric composition. This project uses spare CPU time on volunteers' personal computers to run the regional climate model (RCM) HadRM3P nested in the HadAM3P atmospheric general circulation climate model (AGCM)[9] driven with prescribed sea surface temperatures (SSTs) and sea ice concentration (SIC). The RCM covers Europe and the Eastern North Atlantic Ocean, at a spatial resolution of about 50 km. 17,367 winters (December, January and February: DJF) were simulated under observed 2013/2014 GHG concentrations, SSTs and SIC ("Actual Conditions"). Initial conditions are perturbed slightly for each ensemble member on December 1 to give a different realisation of the winter weather[9]. The remaining simulations ("Natural") represent different estimates of conditions that might have occurred in a world without past emissions of GHGs and other pollutants including sulphate aerosol precursors. In the Natural simulations, atmospheric composition is set to pre-industrial, the maximum well-observed SIC is used (DJF 1986/1987, the precise choice is unimportant: Supplementary Fig. 5) and estimated anthropogenic SST change patterns are removed from observed DJF 2013/2014 SSTs. To account for the uncertainty in our estimates of a world without anthropogenic influence, 11 different patterns are calculated from GCM simulations of the Coupled Model Intercomparison Project phase 5 (CMIP5)[10] (Supplementary Information Section 2). We include all CMIP5 models with at least 3 ensemble members available regardless of how well their simulated trends fit observed SST trends in the North Atlantic, to provide a conservative estimate of uncertainty.

We consider January precipitation and SLP, with Southern England Precipitation (SEP) averaged over land grid points in 50º–52ºN, 6.5ºW–2ºE. Simulated anomalies for Actual Conditions ensemble members with the wettest 1% SEP, i.e. return periods of 1-in-100-year and rarer, are comparable to observations of January 2014, consistent with previous model evaluation[9] (Fig. 1c-d). The mean climate of the RCM has a wet bias of ~0.4 mm day^{-1} in January over Southern England[9] but most RCM simulations for January 2014 show smaller anomalies than observed, and show a weaker SLP pattern for the same precipitation anomaly (Fig. 1c-d). On average, the Actual Conditions simulations reproduce a stronger jet stream, compared to the 1986-2011 climatology, of January 2014 in the North Atlantic (ERA-Interim[11], Fig. 2a-b), suggesting some potential predictability for the enhanced jet stream of January 2014. The differences in SSTs, SICs and atmospheric composition between Actual Conditions and Natural simulations lead to an increase of up to 0.5 mm day^{-1} in the wettest 1% ensemble members for January SEP (Supplementary Fig. 8). While a warmer atmosphere holds more water vapour, causing an increase in risk of heavy winter rainfall, a dynamic effect where anthropogenic forcings altered probability of occurrence of the atmospheric circulation that favoured the winter 2013/2014 conditions[12] is also possible. Disentangling whether a change in precipitation extremes is caused by anthropogenic forcing via thermodynamic or dynamic processes remains a major challenge[3,13], which we now address.

2. Relationships between atmospheric circulation and precipitation

To investigate the joint changes in precipitation and circulation, the observed and modelled Atlantic flows are classified into four main weather regimes using a classical cluster analysis[14-16] (Supplementary Information Section 3). During January 2014, the atmospheric circulation was classified on 26 out of 31 days as “zonal regime” (ZO). This is the highest ZO occupancy in January since 1871 (Supplementary Fig. 7f). The winter as a whole also set a record (70% of days in ZO), in both cases with record low pressure northwest of Scotland (20°W, 60°N, the centre of the anomaly associated with the ZO regime, Supplementary Fig. 7b, and where SLP is strongly associated with SEP, Supplementary Fig. 2a). In the following we use these two circulation indices - the January average sea level pressure Northwest of Scotland and the number of days spent in the ZO regime - to characterize the circulation and its changes. In the RCM simulations, anthropogenic forcing is found to affect the joint distribution of precipitation in Southern England with both low pressure and ZO occupancy (Figs 4a-b). The joint distribution of the Actual Conditions ensemble is stretched towards lower pressures (higher ZO occupancies) and higher precipitation compared to the pooled Natural ensemble, while the other end of the joint distribution (lower precipitation and higher pressure) is unaffected. The model shows more low-pressure systems and days in the ZO regime in the current climate than in the counterfactual world without human influence on climate, with correspondingly higher monthly precipitation amounts in Southern England. Fig. 5a shows the return period (i.e. the inverse of the tail probability) of the pressure index values for all ensembles. Comparing return periods in the Actual Conditions and Natural ensembles gives the change in risk. The risk of experiencing a 1-in-100-year low-pressure event Northwest of Scotland in the Actual Conditions ensemble increases by a best estimate of 55% due to climate change (with an uncertainty range of no change to over 120% increase). We have used all ensemble members available from the individual Natural simulations as our best estimate (Supplementary Information Section 2 discusses this choice and sensitivity of our results to it).

This change in risk is of similar amplitude to the difference from the 1986-2011 climatology (grey dots) and implies that the anomalous circulation in January 2014 was both a response to the January 2014 SSTs and sea ice concentration, hence potentially predictable, and influenced by anthropogenic forcing.

Even with these SSTs, however, it still appears to have been relatively unlikely: monthly ZO occupancy of 24 days have on average a return period of 1-in-151-year in the pre-industrial climate (uncertainty range: 1-in-104-year to 1-in-230-year), which changes to 1-in-113-year due to climate change (Fig. 5b). Flows under the ZO regime have an eastward-extended jet stream towards European coasts. A higher frequency of ZO regimes is thus consistent with recent studies of the effect of climate change on limiting large latitudinal fluctuations of the jet-stream[17], thereby favouring occupancy of regimes like ZO, in line with Ref 18. Our results are not inconsistent with studies reporting insignificant future mean changes of the North Annular Mode or North Atlantic Oscillation (NAM/NAO)[17,19] because we are detecting a weak signal in extremes, in a much larger ensemble than previously used.

To examine changes in the frequency of extreme precipitation events, we use RCM outputs for the Southern England region and average observations from 8 stations in this region with long records in Met Office archives. Using the time series from 1912-2013 for these 8 stations alone (Supplementary Fig. 1) and treating individual months as independent, the best estimate of the return period of January 2014 SEP is around 85 years (90% confidence interval of 35-550 years; Fig. 5c). Observed Southern England monthly winter precipitation amounts show no statistically significant change in extreme values between the recent period and a century ago using a simple statistical model, although the sensitivity of the test is low (Supplementary Information Section 4).

In the large RCM ensemble, the best estimate for the overall change in risk of a 1-in-100-year January precipitation event pooling all the Natural simulations is an increase of 43%, with a range from no change to 164% increase associated with uncertainty in the pattern of anthropogenic warming (Fig. 5d). Supplementary Fig. 5 shows that this uncertainty is mainly caused by the difference in SSTs and is not affected by the exact choice of sea ice conditions. The potential predictability identified for the pressure index (Fig. 5a) does not appear to extend to precipitation for which the climatological distribution is consistent with the Actual Conditions ensemble. The Natural ensemble with the smallest change in risk of 1-in-100-year precipitation between Actual and Natural conditions (with the SST pattern from the HadGEM2-ES model) also shows a similar jet stream anomaly to the Actual Conditions ensemble (Fig. 2c). There is no such anomaly in the Natural ensemble showing the greatest change in this risk (with the SST pattern from the CCSM4 model, Fig. 2d).

The 11 estimates of the SST response to anthropogenic forcing allow a statistical investigation into the drivers of the dynamic response. The obvious candidate indices are the global-mean warming and the anthropogenic change in meridional SST gradient upstream (since mid-latitude cyclones are forced by the atmospheric meridional temperature gradient). We represent the latter by the difference between the regions 30ºN–50ºN, 40ºW–0ºW and 50ºN–70ºN, 40ºW–0ºW. Correlations across the 11 anthropogenic SST change patterns of the change in 1-in-100-year SEP with the global-mean warming and the anthropogenic change in meridional SST gradient upstream are 0.73 and 0.74 (in line with previous studies[20,21]) respectively (notional *p*-value of 0.01 using a *t*-test). As expected, these two indices are themselves correlated, but only at 0.44 (p-value of 0.17). Dividing the change in gradient by the global-mean warming to leave only the pattern of change, not of its magnitude, still gives a correlation of 0.69 (p-value of 0.02). Thus both large-scale warming and local dynamical changes play a role.

We estimate the relative importance of thermodynamic and dynamic effects by using the pressure index as a proxy for the changes in circulation between Actual Conditions and Natural simulations. By weighting the Natural ensemble members to match the distribution of the Actual Conditions pressure index values (Fig. 4c and Supplementary Information Section 5) and applying this weighting to the precipitation index to remove the effect of circulation (Fig. 4d), we estimate that the increase in risk of the 1-in-100-year precipitation event due to anthropogenic forcing is caused approximately 2/3 by thermodynamic changes, and approximately 1/3 by circulation changes. Previous studies such as Ref 3 found only a thermodynamic influence.

3. Attributing changes in impacts

Modelled precipitation and temperature are fed into the CLASSIC hydrological model of the Thames catchment[22], spun up with observed data from January 2010 to early December 2013 (Supplementary Information Section 6).

For a 1-in-100-year event in the hydrological model, anthropogenic climate change increased the modelled risk of 30-day peak river flows at Kingston by a best estimate value of 21% (uncertainty range: -12% to 133%) (Fig. 5e). For daily peak flows however, the increase was a best estimate of 4% (uncertainty range: -17% to 30%). The impacts on daily peak flows are moderated by changes in snow (Supplementary Section 6.4). Snow has historically been one of the primary flood-generating mechanisms in the lower Thames (typically via rapid melt of large accumulations coincident with heavy rainfall, as occurred to cause the major flooding of March 1947), but has been less common in recent years[23]. However, the other primary flood-generating mechanism in the lower Thames is sustained heavy rainfall (typically over 4-7 days) on saturated ground[23]. Thus differences in the anthropogenic influence on extreme 5-day and 30-day rainfall accumulations (Supplementary Fig. 14) further explain the more modest impacts on daily peak flows compared to 30-day peak flows. These differences between 30-day and 5-day rainfall accumulations are correlated with the SST gradients of the 11 Natural ensembles at 0.65 (p-value of 0.03). Thus the anthropogenic increase in rainfall that we simulate is less on timescales that dominate flooding in this catchment, consistent with the mechanism being an increase in the frequency of the zonal regime, and so, successions of strong but fast-moving storms.

Outputs from CLASSIC are combined with information about the location of properties at risk of flooding in the Thames catchment, for flood events of various magnitudes, in order to estimate the change in risk of numbers of properties (Supplementary Information Section 7). These estimates are derived using a method previously applied in the production of official government flood zone maps in England[24] (incorporating subsequent improvements in data and modelling). The Ordnance Survey, the government agency responsible for mapping of Great Britain, supplied property location data. Changes in risk are reported here based on the daily peak flows, which represent the closest available approximation to the instantaneous peak flow rates that determine river water levels, even though the effects of changes in forcing are greater for flow volumes integrated over longer durations.

For events with around a 100-year return period, the best estimate is that about 1,000 more properties are placed at risk of flooding in a human-altered climate (Fig. 5f). Again, the results span a range of possible outcomes from around 4,000 fewer to 8,000 more properties at risk. The average flood insurance claim during the period DJF 2013/2014 (which predominantly reflects flooding in Southern England, especially around the Thames) is reported by industry sources[4] to be approximately £24,000. Therefore the best estimate additional exposure to flood risk in an event similar to DJF 2013/2014 would be about £24 million in terms of potential losses (uncertainty range -£96 million to £192 million) suggesting a non-negligible contribution to risk when taking account of the ensemble uncertainty around the central estimate. Although there is only a small (ensemble average) increase in daily peak flows the results suggest that when winter flooding of the Thames does occur, it could be lasting longer which has implications both for damages and civil emergency management.

The only human influence considered here is the change in atmospheric composition. In both Actual and hypothetical Natural conditions, the flood risk would have been affected by anthropogenic interventions, in particular flood defences, although only a relatively small proportion of floodplain properties benefit from significant defences (Supplementary Information Section 7) and it is not known how that infrastructure might have evolved in the counterfactual world represented in the Natural ensembles.

4. Conclusions

This is the first end-to-end attribution study from anthropogenic changes in atmospheric composition, through a meteorological extreme event and its hydrological impacts to an estimate of the value of those impacts in terms of flood damages. It illustrates how even relatively subtle changes in weather-related risks could potentially have significant monetary impacts. In summary we find that human influence:

- Increased the risk of low pressure Northwest of Britain and the number of days with zonal flow over the North Atlantic
- Increased the risk of heavy precipitation in Southern England
- Increased the chance of extreme 30-day flows for the river Thames
- Had more modest effects on peak daily flows for the river Thames and the risk of flooding to properties in its basin.

All these cases have large uncertainties due to sensitivity to the uncertain geographical pattern of anthropogenic SST warming. We further estimate that while thermodynamic effects cause most of the increase in precipitation, around 1/3 is caused by changes in circulation.

Our results illustrate the importance of considering changing risks of extreme weather in quantifying climate change impacts and highlights that a holistic assessment of the risk requires the consideration of both the thermodynamic and dynamic response of the climate system to human-induced changes in the atmospheric composition[25,26].

Although the central estimate of increase in the number of properties at risk is small, the ensemble uncertainty spans a range of changes in flood damages that includes some chance of reductions, and also a substantial chance of increased damages that would be significant relative to total flood claims during DJF 2013/2014. A broader assessment could include the risks from storm surge in the Thames estuary and from a wider range of extreme weather and flood events. It should be noted that this analysis does not take into account other factors that influence the risk of flooding to properties in southern England, such as continuing development on flood plains and levels of spending on flood defences that have been criticized as inadequate[27], and that some residual risk of flooding will need to be managed under investment strategies regarded as economically optimal[28,29]. It should also be noted that the impacts on flows and damages for other catchments are likely to differ from those estimated for the Thames catchment draining to Kingston, because of differences in catchment characteristics and potential spatial differences in rainfall patterns.

This study is based on one particular atmospheric model where physical model uncertainty is represented only by the differing SST patterns representing the difference between current and pre-industrial obtained from 11 different climate models. It would clearly be desirable to replicate these results with a broader range of climate models to better understand the sensitivities to model formulations as well as biases and forcings, including model resolution and the pattern and magnitude of the anthropogenic SST signal used to simulate the 'climate that might have been' without human influence. Similarly, potential sensitivity of results to the choice of hydrological model should be assessed, although this is likely to be less important than choice of climate model[30]. More studies of this nature are needed if loss and damage from anthropogenic climate change are to be quantified objectively[31] and future assessments of the impacts of climate change are to progress from attributing them simply to changes in climate which are not themselves explained[32], to attributing them specifically to human influence[33].

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Author contributions

NS, AK, RL, GJvO, RV, PY, PAS and MRA designed the study, NS, AK, RL, NRM, AB, JM, JS set up and performed model experiments, NS, AK, RL, NRM, GJvO, FELO, SNS, RV, PY, KH, CH, TL and JS provided analyses and all authors wrote the paper.

Figures

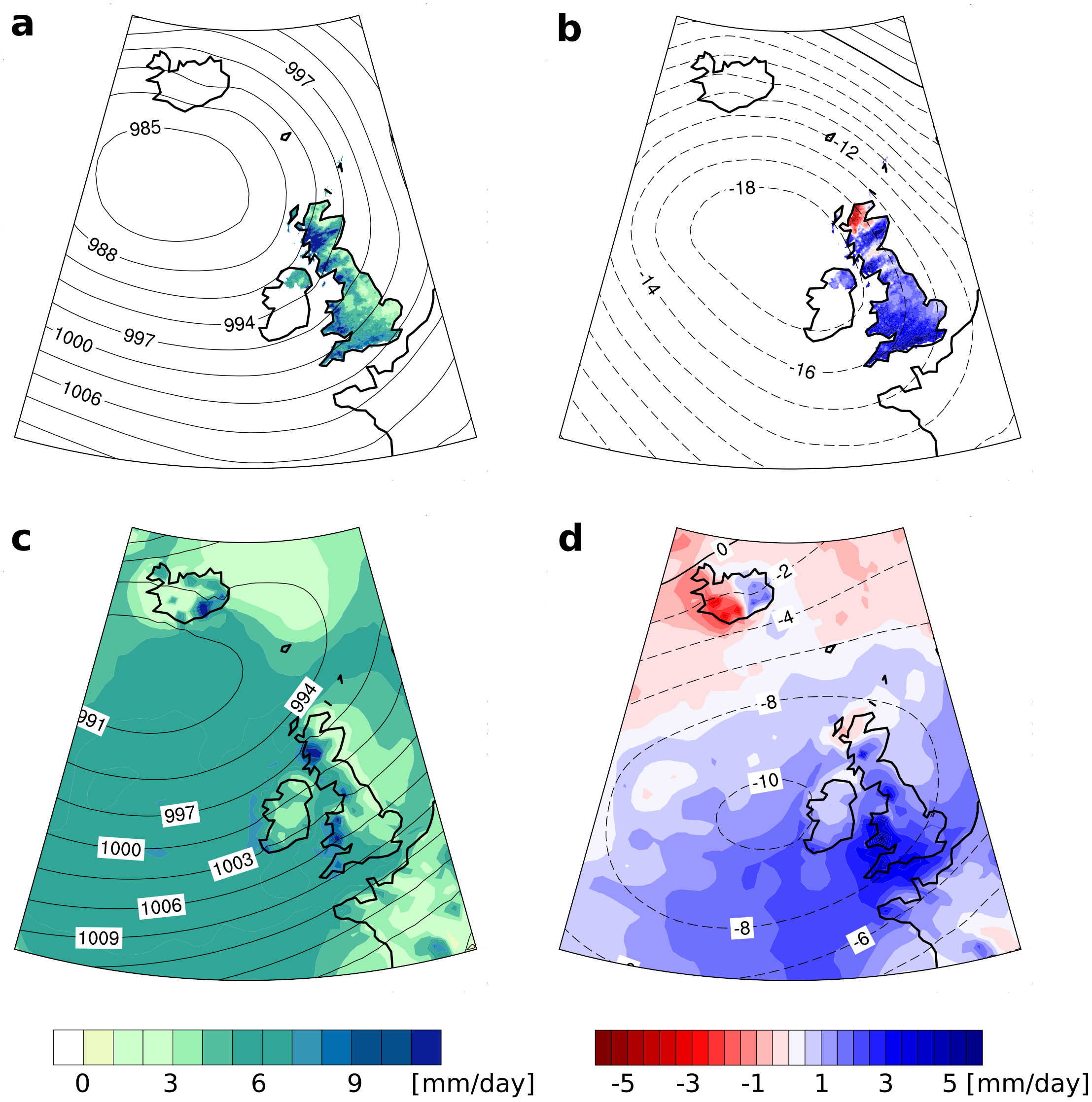

Figure 1: Precipitation[34] (colours, in mm day-1) and mean sea level pressure[11] (contours, in hPa) as observed for January 2014 absolute values in **a** and as anomalies from the observed 1981-2010 climatology in **b**, and in the wettest 1% of the Actual Conditions ensemble as absolute values in **c** and as anomalies from the model 1986-2011 climatology in **d**.

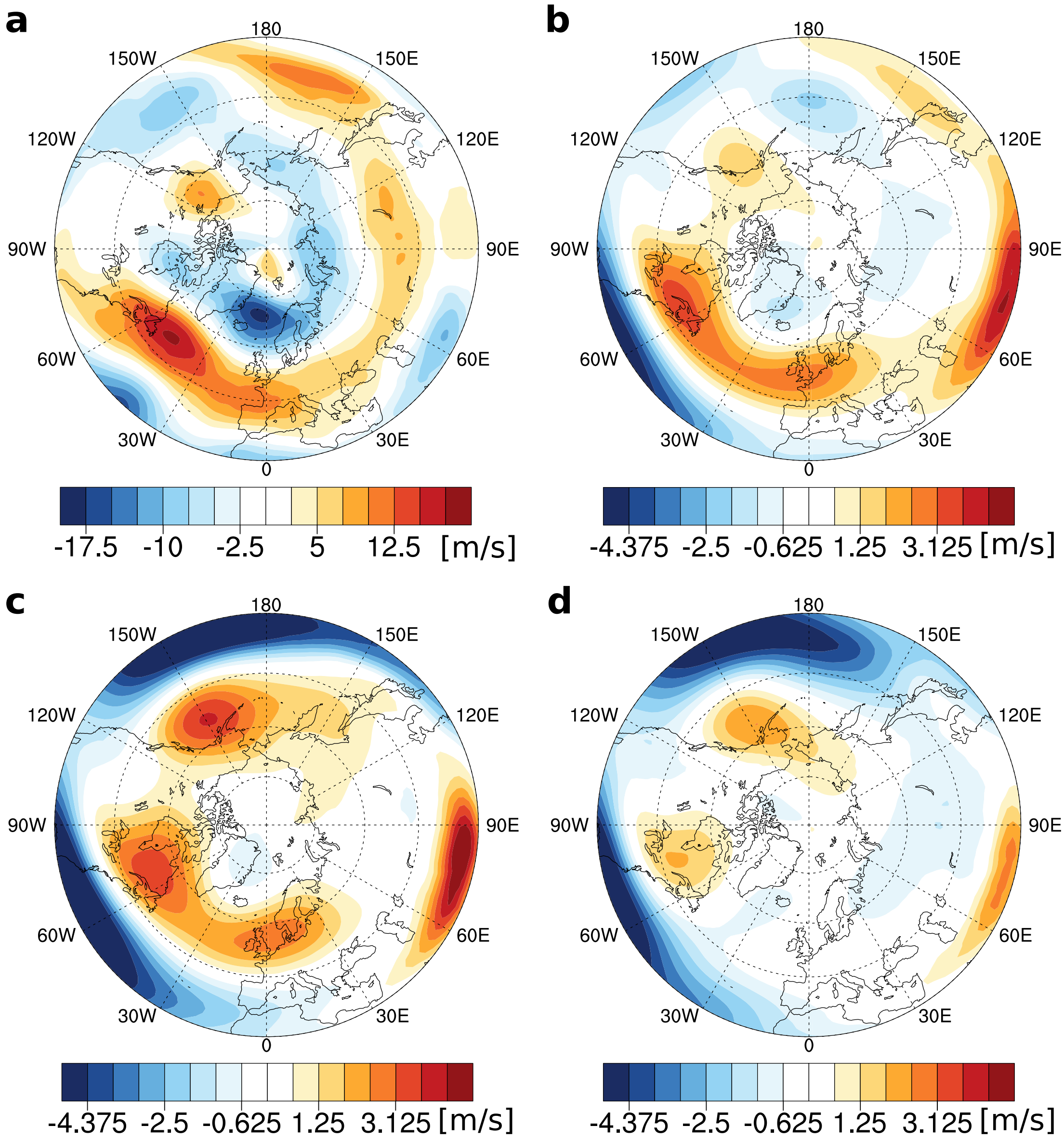

Figure 2: Anomalies of zonal wind at 200 hPa for January 2014 **a** in ERA-interim[11], relative to the 1986-2011 ERA-interim climatology, and **b** in the ensemble mean of the Actual Conditions simulations, relative to the model 1986-2011 climatology. **c** and **d**, as **b**, but for the ensemble means of the Natural simulations with the HadGEM2-ES and CCSM4 models respectively.

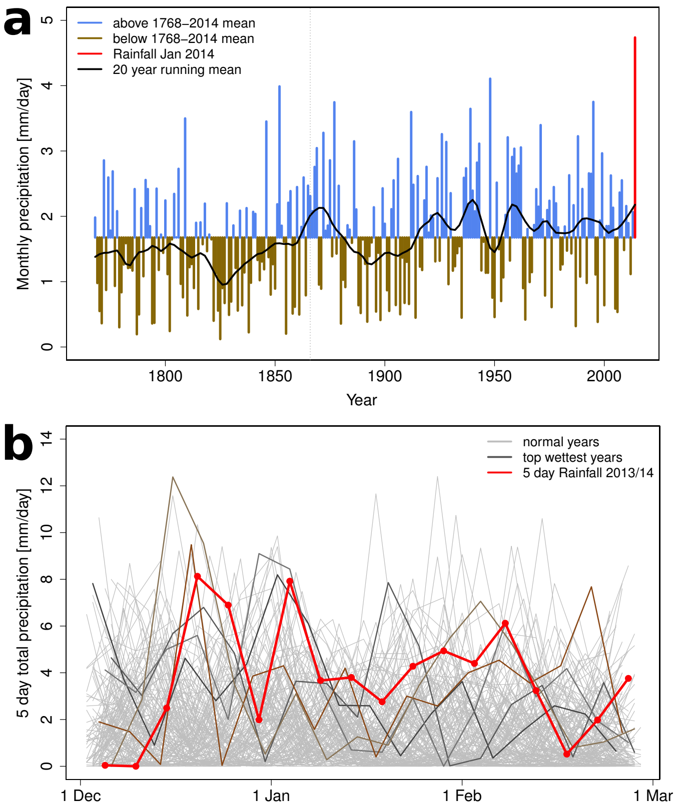

Figure 3: a Time series of monthly mean rain/precipitation for January 1768-2014 at the Radcliffe Observatory, Oxford. Above/below overall average values are plotted in blue/brown. January 2014 is highlighted in red. The black line is the 20-year Lowess-smoothed monthly mean precipitation. The measurements are rain only until around 1867 (dotted thin vertical line), but include snow since then. **b** Comparison of all the 5-day mean precipitation for all winter months from 1827/28-2013/14. The 5 wettest years are highlighted in dark grey. Winter 2013/14 is plotted in red.

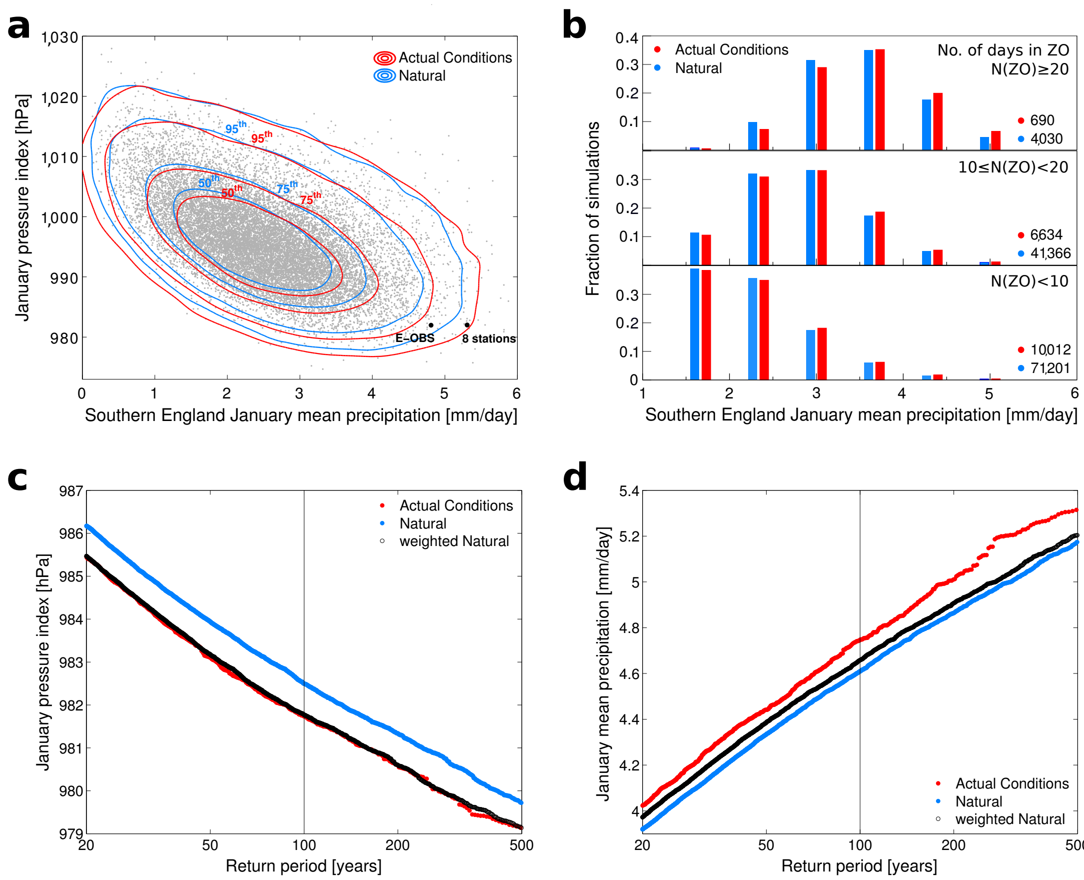

Figure 4: a Relationship between modelled January monthly average Southern England precipitation and mean sea level pressure at 20°W, 60°N. The 50th, 75th, 95th and 99th percentiles of the distribution of the Actual Conditions and all Natural simulations are estimated using a Gaussian bivariate kernel density estimator. Grey dots represent January averages for each individual Actual Conditions simulations and the black dots show values from observations ("8 stations" refers to the average of 8 stations in Southern England for the precipitation index and the NCEP reanalysis[35] for the pressure index, "E-OBS" refers to the same definition as the modelled precipitation index using the gridded E-OBS dataset[36] also with NCEP pressure index). The Actual Conditions and Natural joint distributions are significantly different at the 0.05 level based on a two-sided bivariate version of the Kolmogorov-Smirnov test[37]. **b** As a but showing the relationship between modelled January Southern England precipitation binned in 7 categories and the January ZO index binned in three categories of number of days per month. For all three categories, the distributions of Actual Conditions and Natural are statistically different at the 0.05 level, according to both a two-sided Kolmogorov-Smirnov and a two-sided Cramer-von Mises test. The number of ensemble members in each of the three categories is given on the bottom-right corner of each sub-panel. **c** Return periods for pressure for the Actual Conditions and pooled Natural simulations along with pooled Natural weighted to make its pressure values match the Actual Conditions simulation. **d** as **c** but for precipitation, using the same weights as in **c**.

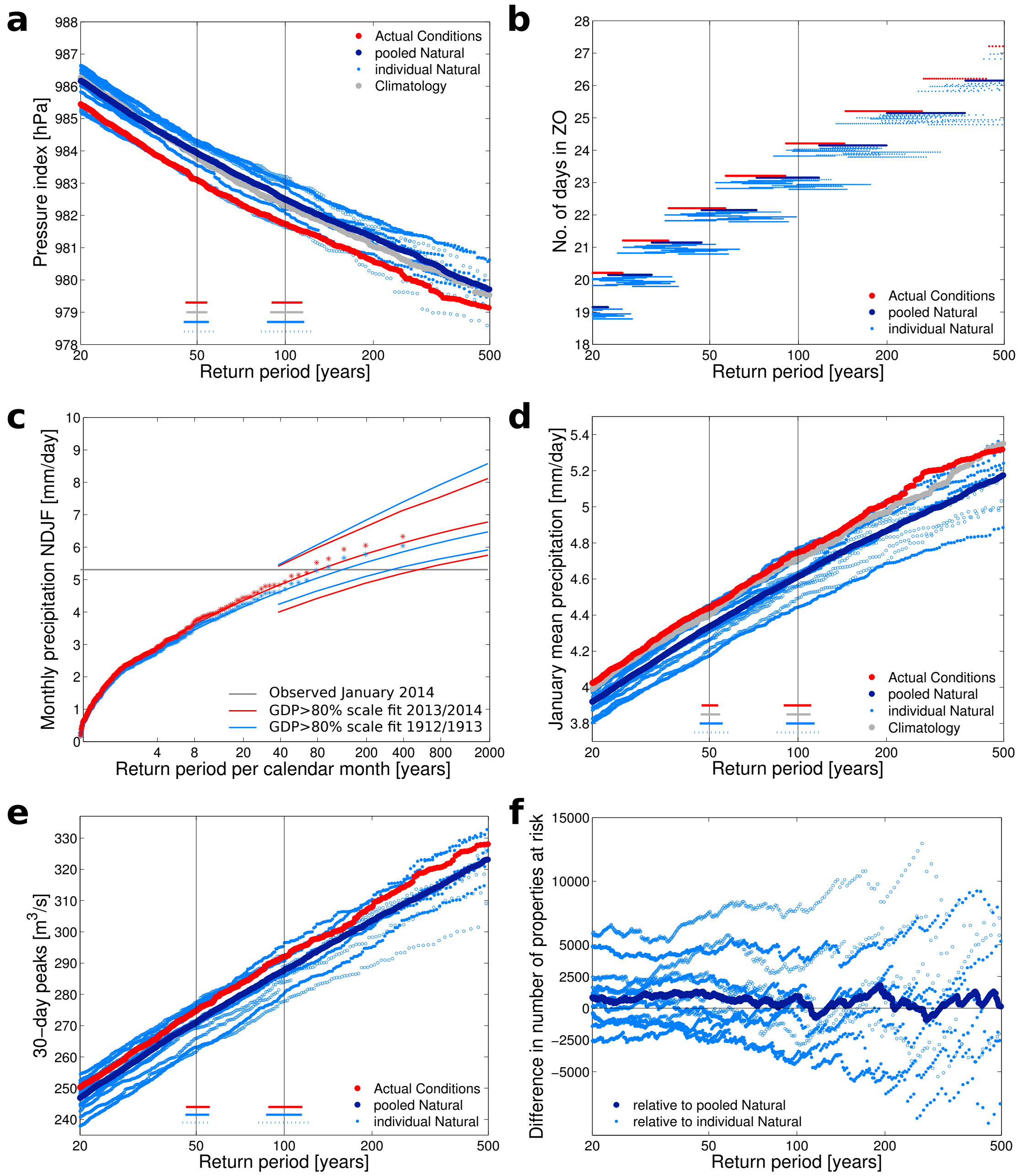

Figure 5: Return periods for **a** modelled January pressure index (each dot represents an ensemble member) with 5-95% confidence intervals for 1-in-50-year events and 1-in-100-year events in Actual Conditions estimated by resampling the distribution 100 times represented as horizontal lines. Red represents Actual Conditions simulations, grey a similar ensemble but for 1986-2011 (the model climatology), dark blue the pooled Natural simulations, and light blue individual Natural (sub-) ensembles, with solid circles for the 6 of the 11 Natural ensembles with around 15,000 simulations, and empty circles for the other 5 with around 7,000 simulations. Only four 5-95% confidence intervals for 1-in-50-year events and 1-in-100-year events (red: Actual Conditions, grey: Climatology, light blue: Natural ensembles with around 15,000 ensemble members and dashed light blue: Natural ensembles with around 7,000 simulations) are shown because the confidence intervals represent only the sampling uncertainty, not the uncertainty in the estimation of the model simulations. **b** as **a** but modelled

frequency of the ZO regime. No confidence intervals are shown due to the categorical nature of return values. **c** observed monthly precipitation averaged for 8 stations across Southern England for the months of November to February individually for the years 1912-2013 fitted to a Generalised Pareto Distribution with location and scale parameters linearly dependent on the low-pass filtered global mean temperature. Red lines indicate the fit and 90% confidence interval for the current temperature (2013/2014), blue for a temperature representative of pre-industrial conditions (1912/1913). The red (blue) crosses show the observations shifted up (down) to these years using the fitted trend. The horizontal grey line represents the observed value for January 2014. The fit has been performed for monthly means of four calendar months to increase the sample size, the return period is given per month for comparison with the other results. **d** as **a** for modelled January mean precipitation in Southern England, **e** as **a** for modelled 30-day peak flows for the Thames at Kingston, and **f** difference between the Natural and the Actual Conditions simulations in number of properties individually at risk of flooding with annual probability 1/*T*, where *T* is the return period.

References

1 Huntingford, C. *et al.* Potential influences on the United Kingdom's floods of winter 2013/14. *Nature Climate Change* **4**, 769-777, doi:10.1038/nclimate2314 (2014).

2 Matthews, T., Murphy, C., Wilby, R. L. & Harrigan, S. Stormiest winter on record for Ireland and UK. *Nature Climate Change* **4**, 738-740 (2014).

3 Pall, P. *et al.* Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature* **470**, 382-385 (2011).

4 Association of British Insurers, https://www.abi.org.uk/Insurance-and-savings/Topics-and-issues/Flooding/2014-floods-in-numbers (Accessed September 2015)

5 Association of British Insurers, https://www.abi.org.uk/News/News-releases/2010/11/massive-rise-in-britains-flood-damage-bill-highlights-the-need-for-more-help-for-flood-vulnerable-communities-says-the-abi.aspx (Accessed September 2015)

6 http://www.bbc.co.uk/news/uk-politics-25656426

7 Stott, P. A., Stone, D. A. & Allen, M. R. Human contribution to the European heatwave of 2003. *Nature* **432**, 610-614, doi:10.1038/nature03089 (2004).

8 Kay, A. L., Crooks, S. M., Pall, P. & Stone, D. A. Attribution of Autumn/Winter 2000 flood risk in England to anthropogenic climate change: A catchment-based study. *Journal of Hydrology* **406**, 97-112, doi:10.1016/j.jhydrol.2011.06.006 (2011).

9 Massey, N. *et al.* weather@home - development and validation of a very large ensemble modelling system for probabilistic event attribution. *Quarterly Journal Of The Royal Meteorological Society*, doi:10.1002/qj.2455 (2014).

10 Taylor, K. E., Stouffer, R. J. & Meehl, G. A. An Overview of CMIP5 and the Experiment Design. *Bull. Amer. Meteorol. Soc.* **93**, 485-498 (2012).

11 Dee, D. P. *et al.* The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society* **137**, 553-597 (2011).

12 van Haren, R., van Oldenborgh, G. J., Lenderink, G. & Hazeleger, W. Evaluation of modeled changes in extreme precipitation in Europe and the Rhine basin. *Environ. Res. Lett.* **8**, 7, doi:10.1088/1748-9326/8/1/014053 (2013).

13 van Haren, R., van Oldenborgh, G. J., Lenderink, G., Collins, M. & Hazeleger, W. SST and circulation trend biases cause an underestimation of European precipitation trends. *Climate Dynamics* **40**, 1-20, doi:10.1007/s00382-012-1401-5 (2013).

14 Vautard, R. Multiple weather regimes over the North Atlantic - Analysis of precursors and successors. *Mon. Weather Rev.* **118**, 2056-2081, doi:10.1175/1520-0493(1990)118<2056:mwrotn>2.0.co;2 (1990).

15 Michelangeli, P. A., Vautard, R. & Legras, B. Weather regimes - Reccurence and quasi stationarity. *J. Atmos. Sci.* **52**, 1237-1256, doi:10.1175/1520-0469(1995)052<1237:wrraqs>2.0.co;2 (1995).

16 Yiou, P., Goubanova, K., Li, Z. X. & Nogaj, M. Weather regime dependence of extreme value statistics for summer temperature and precipitation. *Nonlinear Process Geophys.* **15**, 365-378 (2008).

17 Barnes, E. A. & Polvani, L. Response of the Midlatitude Jets, and of Their Variability, to Increased Greenhouse Gases in the CMIP5 Models. *Journal of Climate* **26**, 7117-7135 (2013).

18 Zappa, G., Hoskins, B. J. & Shepherd, T. G. Improving Climate Change Detection through Optimal Seasonal Averaging: The Case of the North Atlantic Jet and European Precipitation. *Journal of Climate* **28** (16) (2015).

19 Cattiaux, J. & Cassou, C. Opposite CMIP3/CMIP5 trends in the wintertime Northern Annular Mode explained by combined local sea ice and remote tropical influences. *Geophysical Research Letters* **40** (2013).

20 Rodwell, M. J., Rowell, D. P. & Folland, C. K. Oceanic forcing of the wintertime North Atlantic Oscillation and European climate. *Nature* **398**, 320-323, doi:10.1038/18648 (1999).

21 Haarsma, R. J., Selten, F. & van Oldenborgh, G. J. Anthropogenic changes of the thermal and zonal flow structure over Western Europe and Eastern North Atlantic in CMIP3 and CMIP5 models. *Climate Dynamics* **41**, 2577-2588, doi:10.1007/s00382-013-1734-8 (2013).

22 Crooks, S. M. & Naden, P. S. CLASSIC: a semi-distributed rainfall-runoff modelling system. *Hydrol. Earth Syst. Sci.* **11**, 516-531 (2007).

23 Marsh, T. & Harvey, C.L. 2012. The Thames flood series: a lack of trend in flood magnitude and a decline in maximum levels. Hydrology Research, **43**(3), 203-214

24 Bradbrook, K., Waller, S., & Morris, D. National floodplain mapping: Datasets and methods - 160,000 km in 12 months. Natural Hazards, 36(1-2), 103-123 (2005).

25 Trenberth, K., Fasullo, J. T. & Shepherd, T. G. Attribution of climate extreme events. *Nature Climate Change* **5**, 725-730, doi:10.1038/nclimate2657 (2015).

26 Hansen, J., Sato, M. & Ruedy, R. Perception of climate change. *PNAS* **109** (37), E2415-2423, doi:10.1073/pnas.1205276109 (2012).

27 Crichton D. Flood Risk and Insurance in England and Wales: Are there lessons to be learned from Scotland? (Benfield Hazard Research Centre, UCL, London, 2005).

28 Committee on Climate Change. Managing climate risks to well-being and the economy. (Adaptation Sub-Committee Progress Report, Committee on Climate Change, London, 2014). http://www.theccc.org.uk/wp-content/uploads/2014/07/Final_ASC-2014_web-version-4.pdf (Accessed September 2015)

29 Environment Agency. Flood and coastal erosion risk management. (Long-term investment scenarios, Report No. LIT10045, Environment Agency, Bristol UK, 2014). https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/381939/FCRM_Long_term_investment_scenarios.pdf (Accessed September 2015)

30 Kay, A. L., Davies, H. N., Bell, V. A. & Jones, R. G. Comparison of uncertainty sources for climate change impacts: flood frequency in England. *Climatic Change* **92**, 41-63, doi:10.1007/s10584-008-9471-4 (2009).

31 James, R. *et al.* Characterizing loss and damage from climate change. *Nature Clim. Change* **4**, 938-939, doi:10.1038/nclimate2411 (2014).

32 Cramer, W. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds C. B. Field *et al.*) (Cambridge University Press, 2014).

33 Bindoff, N. L. *et al.* in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds T. F. Stocker *et al.*) (Cambridge University Press, 2013).

34 Perry, M. & Hollis, D. The generation of monthly gridded datasets for a range of climatic variables over the UK. *Int. J. Climatol.* **25**, 1041-1054, doi:10.1002/joc.1161 (2005).

35 Kistler, R. *et al.* The NCEP-NCAR 50-year reanalysis: Monthly means CD-ROM and documentation. *Bull. Amer. Meteorol. Soc.* **82**, 247-267, doi:10.1175/1520-0477(2001)082<0247:tnnyrm>2.3.co;2 (2001).

36 Haylock, M. R. *et al.* A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. *J. Geophys. Res.-Atmos.* **113**, D20119-D20119 (2008).

37 Peacock, J. A. Two-dimensional goodness-of-fit testing in astronomy. *Mon. Not. Roy. Astron. Soc.* **202**, 615-627 (1983).