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LETTER

The timing of anthropogenic emergence in simulated climate extremes

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Abstract

Determining the time of emergence of climates altered from their natural state by anthropogenic influences can help inform the development of adaptation and mitigation strategies to climate change. Previous studies have examined the time of emergence of climate averages. However, at the global scale, the emergence of changes in extreme events, which have the greatest societal impacts, has not been investigated before. Based on state-of-the-art climate models, we show that temperature extremes generally emerge slightly later from their quasi-natural climate state than seasonal means, due to greater variability in extremes. Nevertheless, according to model evidence, both hot and cold extremes have already emerged across many areas. Remarkably, even precipitation extremes that have very large variability are projected to emerge in the coming decades in Northern Hemisphere winters associated with a wettening trend. Based on our findings we expect local temperature and precipitation extremes to already differ significantly from their previous quasi-natural state at many locations or to do so in the near future. Our findings have implications for climate impacts and detection and attribution studies assessing observed changes in regional climate extremes by showing whether they will likely find a fingerprint of anthropogenic climate change.

1. Introduction

Overall, the anthropogenic influence on the climate is causing the Earth to warm and the statistical properties of temperature and precipitation to change. In terms of impacts, changes in the climate become most relevant when a novel climate emerges (i.e. the climate of a certain period differs significantly from that of an undisturbed state). This has motivated investigations of the 'time of emergence' which is the point in time when observations or model simulations show a significant difference from a chosen baseline period, e.g. the last 30 yr. Previously, efforts to calculate time of emergence have focused on mean temperature and precipitation (Giorgi and Bi 2009, Mahlstein *et al* 2011, 2012a, 2012b, Hawkins and Sutton 2012) and recently, sea level rise (Lyu *et al* 2014). Investigations into the time of emergence of extreme temperatures over the United States (Scherer and Diffenbaugh 2014) and extreme precipitation over Europe (Maraun 2013) found robust signs of emergence in the coming decades. However, the time of emergence is expected to strongly differ across different regions of the globe. Previous studies have often used model-based signal-to-noise ratios (Hawkins and Sutton 2012) or exceedance of a median value (Diffenbaugh and Scherer 2011) to determine when the future mean climate emerges from its present-day

Table 1. Definitions of mean and extreme indices used in this analysis.

Mean and extreme indices	Definition of index
Tas	Seasonal mean temperature
Pr	Seasonal total precipitation
TXx	Highest daily maximum temperature per season
TXn	Lowest daily maximum temperature per season
TNx	Highest daily minimum temperature per season
TNn	Lowest daily minimum temperature per season
RX1D	Maximum 1-d precipitation per season
RX5D	Maximum consecutive 5-d precipitation per season

state or recent past. However, these studies did not take into account that the climate has changed over recent decades or implicitly assumed that society is fully adapted to the present-day climate. Here we use a baseline period close to the pre-industrial state, when the anthropogenic influence on the climate was much smaller than today (Mahlstein *et al* 2012a), to calculate a time of anthropogenic emergence (TAE) for climate extremes (table 1) globally. We employ statistical tests to calculate the TAE as the time when distributions of mean and extreme temperatures and precipitation emerge from those seen in the baseline period.

2. Data and methods

Twenty-three model simulations from the Fifth Phase of the Coupled Model Intercomparison Project (CMIP5; Taylor *et al* 2012) combining historical (1860–2005) and RCP8.5 scenario (2006–2099) simulations from six climate models (table S1) were used in this analysis. These six models were selected as they all had mean temperature and precipitation and extreme indices available for at least three historical and RCP8.5 runs. The mean climate was represented by the surface air temperature (tas) and precipitation (pr) variables. The climate extremes indices (Zhang *et al* 2011) used in this study were the seasonal maximum and minimum values of daily maximum temperature (TXx and TXn respectively) and daily minimum temperature (TNx and TNn respectively), and the seasonal maximum 1-d and consecutive 5-d precipitation (RX1D and RX5D respectively). These climate extremes indices, calculated for the different CMIP5 runs, were obtained from the Environment Canada CLIMDEX website (http://cccma.ec.gc.ca/data/climdex/; Sillmann *et al* 2013a, 2013b) and have been used in many studies as measures of climate extremes (e.g. Min *et al* 2011). Monthly values of these mean and extreme variables were regridded onto a common $2.5^\circ \times 2.5^\circ$ grid. Seasonal values (June–August and December–February) were calculated at each gridbox and variable for each model run for 1860–2099, such that the extreme indices represent the maximum (in the case of TXx, TNx, RX1D, and RX5D) or minimum values (in the case of TXn and TNn) for the season.

While the indices studied here might be less 'extreme' than events with longer return intervals (such as 1-in-100 year maximum daily precipitation events which are often used by the hydrological modelling community), they offer a more robust way to analyse the time of emergence results which would otherwise be affected by the small sample sizes of very rare events. Furthermore, they still represent climate extremes that have major impacts on people and infrastructure and are, therefore, of relevance to many industries and sectors. For example, changes in the hottest minimum temperature in the summer or the coldest minimum in the winter are of importance to the health sector as they are linked with increased hospital admissions in many regions (e.g. Lin *et al* 2009).

Within each of the 23 model runs, quasi-natural distributions of each variable were calculated, for each gridbox and season, over the 1860–1910 period when anthropogenic forcing on the climate was much smaller than it is today. A 51-yr period as opposed to a shorter baseline was used to reduce the potential influences of multi-decadal variability on the results and so that the findings would be more robust. Moving windows of 20-yr periods were compiled for the 1920–2099 period and similarity with the quasi-natural distributions was tested using a Kolmogorov–Smirnov (KS-) test with statistical significance defined at the 5% level (Mahlstein *et al* 2012a). The TAE is defined as the year when the KS-test implies that the variable, defined seasonally for the 20-yr windowed period, is drawn from a different distribution than the quasi-natural period, and that all subsequent 20-yr windowed periods are also drawn from different distributions than the quasi-natural period. The nonparametric KS-test is well-suited to these calculations as it can be used to detect differences in the location and shape of two different distributions. This makes it better suited to the study of changes in climate extremes than a signal-to-noise ratio. The TAE is indexed to the first year of the 20-yr moving windows. This method was applied to variables at individual land gridboxes, and averaged over sub-continental regions and the globe as a whole. Median TAE values were calculated at each land gridbox across all 23 model runs. A median TAE rather than a mean TAE was calculated so that the influence of outlier model values is nullified. Although, any systematic biases, such as those that might exist in simulated interannual climate variability, are not accounted for by this method. A comparison between modelled interannual variability and that observed in Australian mean seasonal temperatures found simulated variability to be generally higher. This would suggest that the TAE estimates may be slightly conservative. TAE values after 2060 were classified as not showing emergence because we cannot be sure of permanent emergence beyond the end of the simulations in these cases (e.g. Hawkins *et al* 2014). TAE values were also calculated over the ocean (not shown) producing similar patterns of emergence but tending to show earlier emergence than over adjacent land regions. Ocean TAE values are not shown as the climate extremes considered here are of most relevance to land regions.

The term 'TAE' is used because the same methodology was also applied to mean temperature indices in HistoricalNat simulations where there are no anthropogenic forcings. At all gridboxes, no emergence was seen in a majority of simulations in both boreal summer and winter. These findings demonstrate that the TAE values seen in the historical and RCP8.5 simulations are associated with anthropogenic influences on the climate.

The signal and noise were also calculated on the same spatial scales as TAE values. Signal is defined as the mean difference in each of these variables between 1860–1910 and 1989–2039 (a 51-yr period centred on 2014). Noise is calculated as the interannual standard deviation of each variable for the 1860–1910 quasi-natural period. Latitudinally averaged values of signal and noise are calculated as the mean signal value at each 2.5° latitude band, based on land values only. Again, median values of signal and noise across model runs were calculated.

Pattern correlations (Spearman's rank) of TAE values were calculated between each model simulation for each index. Rank correlation coefficients were calculated, instead of Pearson's correlations, so that an assumption of normality in the distributions was not required.

Times of anthropogenic emergence were also calculated based on a long-running station-based observational timeseries, the Central England temperature series (CET; Parker *et al* 1992), and compared with the model timeseries for the 2.5° gridbox located over Central England, using a similar methodology as applied to the model simulations previously. As the CET minimum and maximum temperatures start in 1878, the model and observed baselines were reduced to the period 1878–1910. The model results were compared with those calculated using the 1860–1910 baseline and the differences in TAE were found to be small. Several long-running stations were investigated but were found to have had changes in instrumentation leading to artificially early TAE values or there was a lack of meta-data about the station's history. Stations with substantial changes in location or instrumentation are likely to have statistical breakpoints in their timeseries, which the KS-test, used in the TAE calculation, could detect and incorrectly associate with anthropogenic climate change. This is especially a problem when studying extremes as adjustments are often made based on the mean only.

Sensitivity tests to choices made in applying this methodology for TAE calculations were conducted (see supplementary text for more details available at stacks.iop.org/ERL/10/094015/mmedia).

3. Results

3.1. CMIP5 model simulations

We find substantially earlier emergence of temperature extremes (defined as the hottest and coldest daily maximum and minimum temperatures in a season) in the tropics than in the extra-tropics (figure 1, S1) despite the warming signal in the tropics being comparatively small. The early tropical emergence, which is also seen in mean temperatures (figure 1, Hawkins and Sutton 2012, Mahlstein *et al* 2012a) is due to the lack of a pronounced seasonal cycle and substantially lower subseasonal and interannual temperature variability in equatorial regions than at higher latitudes. Whilst the temperature changes associated with the early emergence in the tropics are small, they have strong effects on the flora and fauna that exist there (Mora *et al* 2013).

Across the globe, hot and cold temperature extremes tend to emerge later than mean temperatures since they experience larger internal variability. Nevertheless, climate model simulations consistently suggest that over much of the globe the emergence of extreme temperatures has already occurred, and thus is potentially detectable in observations, subject to the limitations of the observational records. Given that these temperature extremes are one-in-one-year events, it is remarkable that the interannual variability is low enough such that an emergence can be detected through the KS-test. For precipitation extremes, on the other hand, the TAE is considerably later or, in many regions, does not occur prior to 2100 (the end of our model simulations). Remarkably, however, an anthropogenic signal is emerging, or is expected to emerge soon, in wintertime heavy precipitation events over much of Eurasia and North America despite large variability in these regions. Hegerl *et al* (2004) found a detectable wettening signal in modelled heavy precipitation events at Northern high latitudes associated with anthropogenic influences on the climate. This emergence of extreme precipitation in winter is associated with a consistent wettening signal in the models (figure S2, see also Fischer *et al* 2014), which can also be seen in observational data (Min *et al* 2011, Donat *et al* 2013).

Whilst all model simulations show broadly similar geographical patterns of TAE, as evidenced by

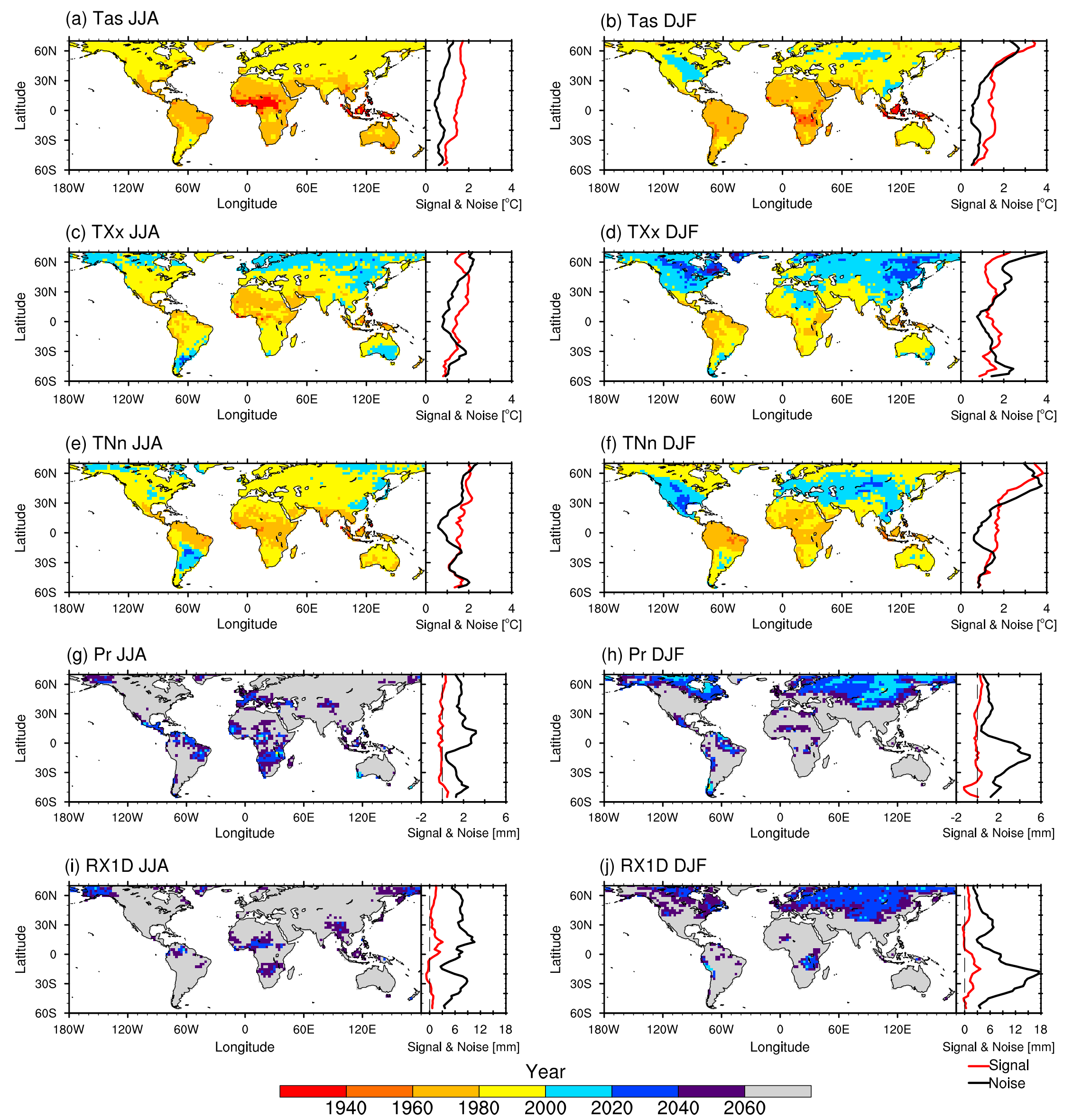

Figure 1. Median time of anthropogenic emergence and zonally averaged signal and noise for climate means and extremes. Maps of median TAE averaged across 23 model simulations for (a) and (b) mean surface air temperature, (c) and (d) highest daily maximum temperature, (e) and (f) lowest daily minimum temperature, (g) and (h) total precipitation, and (i), (j) maximum 1-d precipitation for (a), (c), (e), (g) and (i) June–August and (b), (d), (f), (h) and (j) December–February. Zonally averaged values of signal (red) and noise (black) are shown where signal is the mean difference in the variable between 1989–2039 and 1860–1910, and noise is the standard deviation of the variable for 1860–1910.

generally positive pattern correlations of TAE values between simulations (figure S3), some models simulate earlier emergence (e.g. IPSL-CM5A-LR and MPI-ESM-LR) whereas other models produce later emergence (e.g. CSIRO-Mk3-6-0 and HadGEM2-ES). The reasons for these differences are discussed later. There is spread between models in the climate change signal which is considerably greater than differences in internal variability (figure S4). Whilst there is disagreement between models on the timing of emergence, the agreement on the spatial patterns of TAE between models suggests a greater confidence in where the impacts of anthropogenic climate change are felt first. This is important as it means that the design of adaptation strategies can be targeted towards regions experiencing the earliest impacts from climate change.

To investigate regional differences and uncertainties in the timing of emergence, the TAE was calculated based on area-averaged temperature and precipitation indices for the globe as a whole and subcontinental regions. Calculations were performed on each of the 23 model runs separately and compared. On a global scale, the TAE is considerably earlier for indices based on temperature than for precipitation (figure 2(a)). The TAE occurs before 2014 in all simulations for all mean and extreme temperature indices in June–August (JJA) and December–February (DJF). Both mean and extreme temperature indices have earlier TAE when considering larger spatial scales than the mapped gridbox values. This is caused by a reduction in the noise after indices are spatially aggregated with the effect on extreme indices larger than for

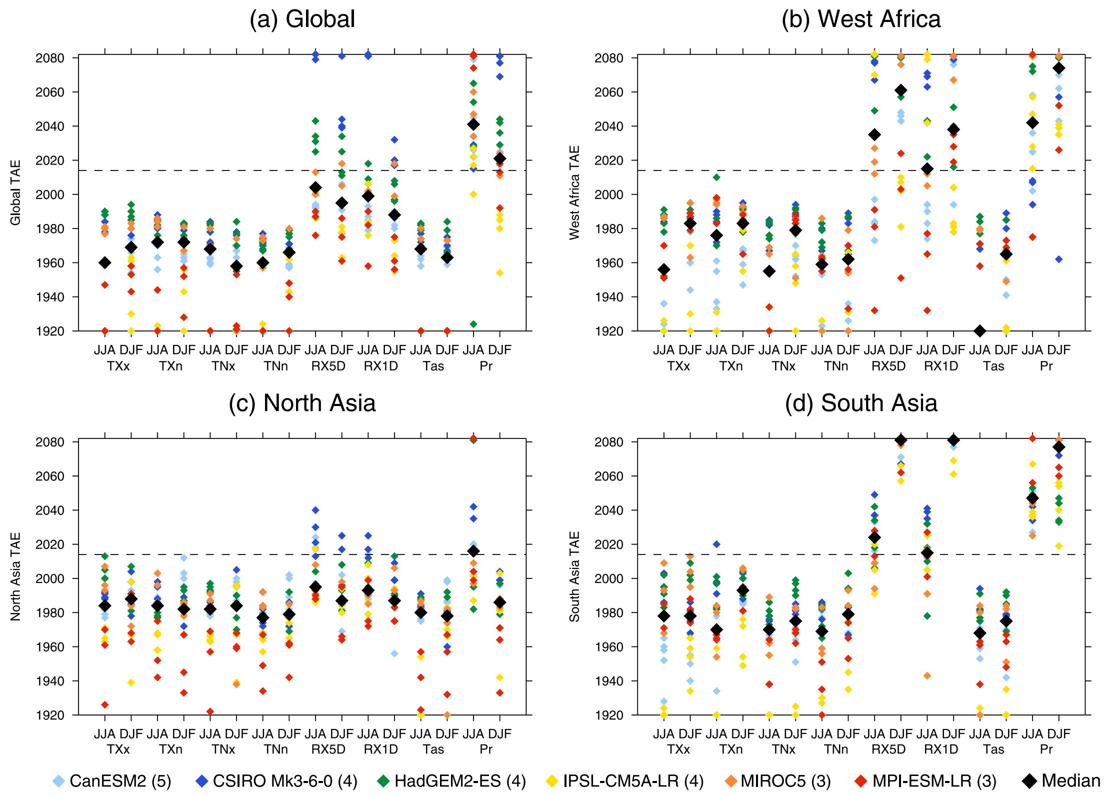

Figure 2. Time of anthropogenic emergence and model uncertainty. Graphs of TAE values for (a) the Globe, (b) West Africa, (c) North Asia and (d) South Asia calculated for each area-averaged extreme and mean index in June–August and December–February shown for CanESM2 (light blue), CSIRO-Mk3-6-0 (dark blue), HadGEM2-ES (green), IPSL-CM5A-LR (yellow), MIROC5 (orange) and MPI-ESM-LR (red). The median value of the 23 model runs is shown in black. The year 2014 is marked by the dashed line.

means (Bell 1982, Deser *et al* 2012, Fischer *et al* 2013). On a global scale there are similar median emergence times for mean and extreme temperatures, but, this is not generally the case at individual gridboxes. Median global TAE for precipitation extremes is around the year 2000 whereas for mean precipitation the TAE has not yet occurred for most model runs. A greater proportion of land-based areas shows a wettening signal in extreme precipitation than in the mean (figure S2). Along with the effect of spatial aggregation reducing noise, this likely explains the earlier global emergence seen in extreme precipitation compared with the mean (Hegerl *et al* 2004).

Understanding regional differences in the time of emergence has potentially useful implications for assessing the impacts of climate change and forming adaptation strategies, so the TAE was also calculated for 21 sub-continental areas of the world (Giorgi and Francisco 2000). For example, in West Africa (figure 2(b)) there is earlier TAE for mean and extreme temperatures than in other parts of the world, but the TAE of precipitation indices is later than in many other regions. Therefore, in this region, adaptation plans would need to be centred on reducing the impacts of extreme heat taking into account local vulnerability and exposures. However, in North Asia (figure 2(c)), the TAE values are more similar across the temperature and precipitation indices. In winter, all model mean precipitation TAEs and most extreme precipitation TAEs are prior to 2014 for North Asia. This is also a region where the range of TAE values, between different simulations, is smaller in precipitation indices than in other areas. In this broad region, adaptation to both the impacts of warming and increasing precipitation would be required. In South Asia (figure 2(d)), there is strong seasonality in TAE of precipitation extremes with earlier emergence in JJA, which coincides with the monsoon season. In all model simulations, heavy 1- and 5-d precipitation emerges earlier in the monsoon season than DJF. This is due to the strong signal towards increased extreme JJA precipitation in the majority of models, whereas in DJF there is virtually no signal (figure S2) and thus no emergence. The strong seasonality seen in emergence of extreme precipitation does not extend to mean precipitation. This analysis was repeated for 18 other sub-continental regions of the world (figure S5) showing earlier emergence of temperature indices than precipitation.

Differences between the TAE values for individual model runs are substantial. The TAE differences are primarily due to model differences rather than internal variability, since differences between individual runs of a single model are smaller than differences

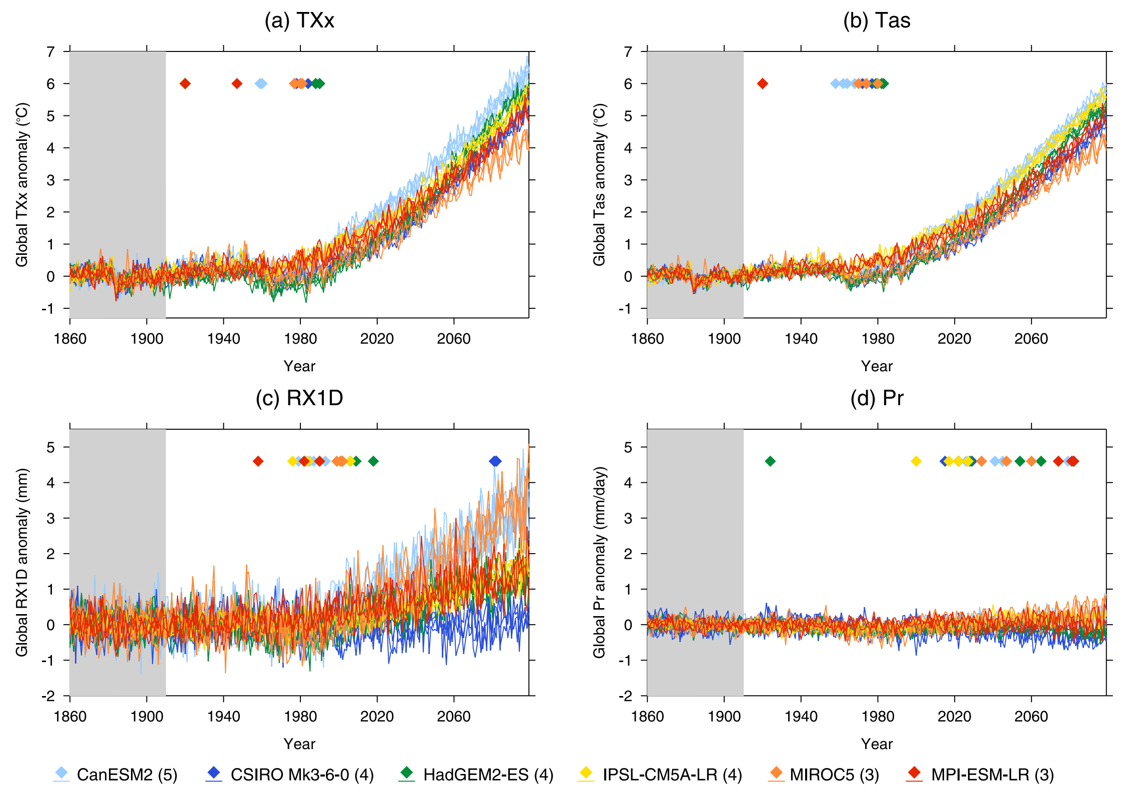

Figure 3. JJA timeseries of globally averaged indices for each model simulation. Timeseries of (a) highest daily maximum temperature, (b) mean temperature, (c) maximum 1-d precipitation, and (d) total precipitation for CanESM2 (light blue), CSIRO-Mk3-6-0 (dark blue), HadGEM2-ES (green), IPSL-CM5A-LR (yellow), MIROC5 (orange) and MPI-ESM-LR (red). TAE values corresponding to each timeseries are shown as diamonds. The baseline period is shown in the grey box. Results based on DJF and the other extreme temperature and precipitation indices are broadly similar (not shown).

between models (figure 2). Differences in TAE values between simulations of the same model are to be expected as internal variability leads to periods of accelerated warming and periods of cooling or reduced warming (e.g. Maher *et al* 2014) that can bring forward or delay the TAE. Similar effects of these 'hiatus' periods on climate extremes have also been found using model simulations (Sillmann *et al* 2014) which will lead to differences in TAE values for extreme indices between simulations of the same climate model. The role of decadal-to-multidecadal variability can be seen through the differences in TAE between simulations of the same model. The principal cause of the large differences in TAE between the climate models is a strong difference in their climate change signal (figure S6), although differences in forcings, in particular in direct and indirect aerosol effects, may play a role. Models with greater signal have earlier TAE values, whereas the relationship between noise and TAE is weak (figure S6(b)). Timeseries of the climate indices give a further indication of the causes of differences between TAE values (figure 3). There is a tendency for models with earlier emergence in means to also have earlier emergence in extremes. Models which exhibit earlier emergence in both mean and extreme temperatures, such as MPI-ESM-LR, show less cooling in the mid-20th century than other models with later emergence, such as HadGEM2-ES (figures 3(a) and (b)). During the mid-20th century there was a period of cooling related to aerosol influences on the climate (Hartmann *et al* 2013). The treatment of these aerosols differs between models and this could explain the different TAE values around this time. Also, the CSIRO Mk3-6-0 model has considerably later emergence times for extreme precipitation than other models related to a lower rate of increase in extreme precipitation on the global scale (figure 3(c)). The large spread between TAE values across these models suggests that different findings could be reached in event attribution studies depending on the selection of models used. Thus, an important consideration when designing an event attribution study may be to select models with a range of climate sensitivities and test the sensitivity of the results to the models used through bootstrapping of simulations. For attribution studies in which an optimal fingerprinting technique is being applied (e.g. Allen and Stott 2003, Min *et al* 2011, Zhang *et al* 2013), the issue of varied signals across models is of less importance due to the regression of observational trends onto fingerprints.

The analysis of TAE values for sub-continental regions of the world allows for the examination of where anthropogenic emergence is detected in climate models prior to 2014 (figure 4). All regions have TAE values prior to 2014 in all or most simulations for

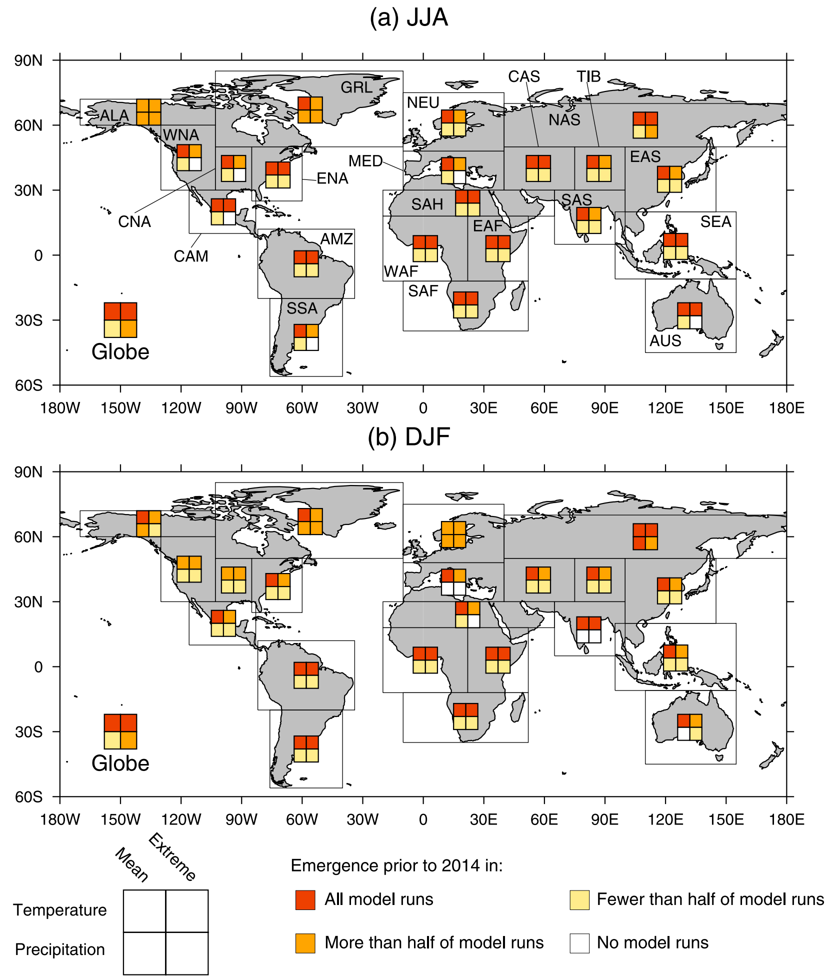

Figure 4. The proportion of models where time of anthropogenic emergence has already occurred. Maps showing the proportion of model simulations with TAE prior to 2014 for each sub-continental region and globally for (a) June–August and (b) December–February. The abbreviated names of the regions (following Giorgi and Francisco (2000)) are shown in (a).

mean and extreme temperature indices. For precipitation, TAEs occurring before 2014 are confined to the Northern Hemisphere high latitudes. These maps are comparable to detection and attribution studies (Christidis *et al* 2005, 2011, Min *et al* 2011, 2013, Morak *et al* 2013, Zhang *et al* 2013), and they provide an indication of whether climate models would suggest a significant anthropogenic influence on extreme temperature and precipitation indices by 2014, and the confidence across the models in there being an anthropogenic signal by this time. For example, if no model runs show emergence prior to 2014 for a given variable and region, a significant anthropogenic signal is unlikely to be detected. Of course, any attribution result will also be influenced by other factors, such as the use of different selections of climate models and different region sizes over which the attribution study is being performed.

3.2. An observational timeseries

An intercomparison of station observations with model simulations was attempted. However, there is a lack of near-complete long-running homogeneous station observations of daily temperature and precipitation extending back into the 19th century (Donat *et al* 2013). TAEs were instead calculated using the CET series, which has extensive literature detailing its history (Parker *et al* 1992). The warming trend in annual mean CET values over recent decades has been attributed to anthropogenic climate change (Karoly and Stott 2006), as has the recent record-breaking 2014 annual CET (King *et al* 2015). Permanent emergence is not clearly seen in either the observational data or model simulations over Central England prior to the present (figure 5). As climate observations only exist to the present unlike model simulations, which can be projected into the future, it is less likely that current observational data will show permanent emergence (i.e. TAE at least a few decades prior to the end of the timeseries). A paucity of long-running homogeneous station data means that a thorough global analysis of the timing of anthropogenic emergence based on observational data would involve using a more recent quasi-natural baseline period, which would include more of an anthropogenic influence on the climate.

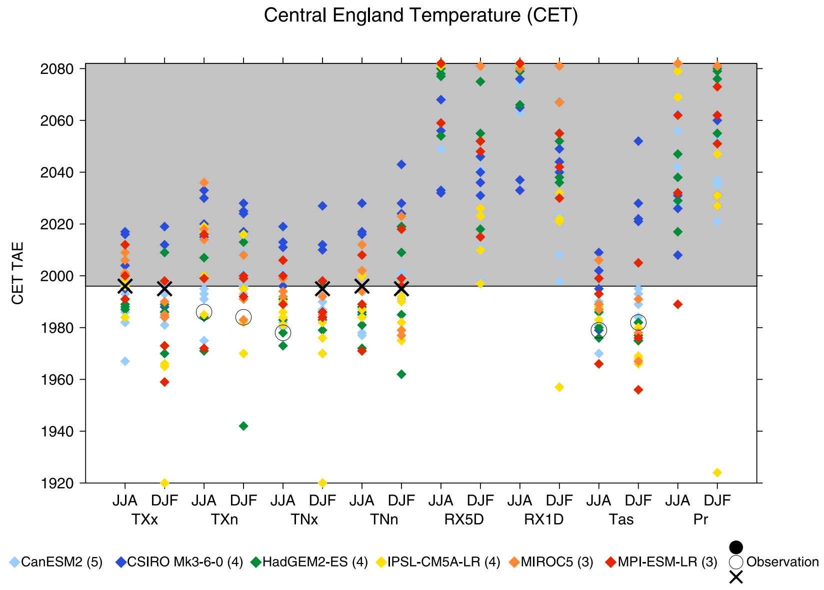

Figure 5. The time of anthropogenic emergence in a long-running observational timeseries. Graph of TAE values calculated using observations for Central England, UK. Crosses indicate no emergence prior to the end of the timeseries, empty circles indicate emergence up to 20 years prior to the end of the timeseries and filled black circles indicate emergence at least 20 years prior to the end of the series. Model TAE values for each extreme and mean index in June–August and December–February at the corresponding gridbox are shown for CanESM2 (light blue), CSIRO-Mk3-6-0 (dark blue), HadGEM2-ES (green), IPSL-CM5A-LR (yellow), MIROC5 (orange) and MPI-ESM-LR (red). The grey box shows the period for which TAE values cannot be determined using the observational data.

4. Conclusions

We present the first global analysis of the time of emergence of climate extremes. The use of a quasi-natural baseline period allows for the calculation of the time of anthropogenic emergence (TAE). This methodology, based on the use of a KS-test, is likely more robust than those based on signal-to-noise ratios (e.g. Hawkins and Sutton 2012, Sui *et al* 2014) as it makes no assumptions about data distributions, which is crucially important for extremes. Generally, the times of emergence are predominantly associated with changes in the location of the distribution, as illustrated by the positive signal values, however, there may be an influence from changes in the shapes of distributions as well. The method, and specifically the use of a pre-industrial baseline period, further allows for associations with the attribution of changes in climate to anthropogenic influences. This study suggests that for much of the world, the anthropogenic emergence of temperature extremes has already occurred as of the present date, at least in model simulations. These findings are in line with those presented in chapter 10 of the IPCC fifth assessment report (Bindoff *et al* 2013) where many regions, for which observations are available, show warming in temperature extremes associated with anthropogenic climate change. The emergence time for temperature extremes is, however, typically later than for mean temperature due to higher interannual variability in extremes compared with the mean. Our study suggests that the changes in these extreme events and their impacts are already being felt across much of the world. For most land-areas, there is no anthropogenic emergence of precipitation extremes prior to the end of this century. However, globally we see emergence and over Northern Hemisphere high latitudes in winter there are signs of emergence of a wettening signal in precipitation extremes in the coming decades.

We show that by examining the TAE we may determine in which regions attribution studies are likely to find an anthropogenic signal as these results suggest whether or not emergence has already occurred. This information is useful in planning for and responding to the impacts of climate change.

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