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Contributions to uncertainty in projections of future drought under climate change scenarios

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Abstract

Drought is a cumulative event, often difficult to define and involving wide reaching consequences for agriculture, ecosystems, water availability, and society. Understanding how the occurrence of drought may change in the future and which sources of uncertainty are dominant can inform appropriate decisions to guide drought impacts assessments. Uncertainties in future projections of drought arise from several sources and our aim is to understand how these sources of uncertainty contribute to future projections of drought. We consider four sources of uncertainty; climate model uncertainty associated with future climate projections, future emissions of greenhouse gases (future scenario uncertainty), type of drought (drought index uncertainty) and drought event definition (threshold uncertainty). Three drought indices (the Standardised Precipitation Index (SPI), Soil Moisture Anomaly (SMA) and Palmer Drought Severity Index (PDSI)) are calculated for the A1B and RCP2.6 future emissions scenarios using monthly model output from a 57 member perturbed parameter ensemble of climate simulations of the HadCM3C Earth system model, for the baseline period, 1961–1990, and the period 2070–2099 (representing the 2080s). We consider where there are significant increases or decreases in the proportion of time spent in drought in the 2080s compared to the baseline and compare the effects from the four sources of uncertainty. Our results suggest that, of the included uncertainty sources, choice of drought index is the most important factor influencing uncertainty in future projections of drought (60 %–85 % of total included uncertainty). There is a greater range of uncertainty between drought indices than that between the mitigation scenario RCP2.6 and the A1B emissions scenario (5 %–6 % in the 2050s to 17 %–18 % in the 2080s) and across the different model variants in the ensemble (9 %–17 %). Choice of drought threshold has the least influence on uncertainty in future drought projections (0.4 %–7 %). Despite the large range of uncertainty in drought projections for many regions, projections for some regions have a clear signal, with uncertainty associated with the magnitude of change rather than direction. For instance, a significant increase in time spent in

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drought is consistently projected for the Amazon, Central America and South Africa whilst projections for Northern India consistently show significant decreases in time spent in drought. We conclude that choice of which drought index (or drought indices) to use when undertaking drought impacts assessments is of considerable importance relative to choices relating to the other three included sources of uncertainty in this study. This information will help ensure that future drought impacts assessments are designed appropriately to account for uncertainty.

1 Introduction

Understanding the potential impacts of climate change is essential if planned responses to avoid or minimise the negative impacts and take advantage of positive impacts are to be successful. It is important to understand potential sources of uncertainty that may influence the trajectory that the future climate takes so that informed decisions can be taken. For instance, knowledge of future uncertainties can be fed into a decision making framework to ensure that responses are appropriate for the range of potential future climates and resultant impacts.

Drought can have far reaching consequences for agriculture, ecosystems, water availability and society. Drought impacts can include water scarcity, crop failure, wildfires and famines (Sheffield and Wood, 2011). Impacts vary with location and are related to the vulnerability of a particular system and its capacity to respond to disasters. For example, severe droughts in modern Australia rarely lead to humanitarian disasters because of the capacity of governments and infrastructure to respond appropriately, whereas droughts in parts of Africa are much more likely to lead to humanitarian disasters because of the greater vulnerability of the affected populations.

Whilst drought is essentially a deficit of moisture, the cumulative nature of drought events coupled with their spatial and temporal variance means that there is no universal definition. In its barest form, drought is a lack of available water related to precipitation, temperature and evaporative demand. Drought occurrence tends to be related

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to climatic extremes and variability (Sheffield and Wood, 2011). A drought is therefore generally defined in terms of its sector of impact, for example an agricultural drought refers to a lack of moisture available to crops. There are four broad types of drought; meteorological drought is a reduction in precipitation relative to the mean for a particular location, hydrological drought relates to a reduction in the availability of surface and sub-surface water, agricultural drought results from an insufficient supply of water for plant growth and includes soil moisture deficit, lastly, socio-economic drought is essentially a combination of the other types of drought that lead to adverse social and economic impacts (Keyantash and Dracup, 2002). Through time, a drought tends to progress from meteorological to agricultural to hydrological (Sheffield and Wood, 2011). These categories are reflected in the many different drought indices that exist, three of which have been used in this study, as outlined in Sect. 3.1.

Droughts have occurred throughout human history and affected the majority of human populations (Sheffield and Wood, 2011). For instance in 2005 there was a severe drought in the Amazon region affecting 280 000 to 300 000 people in Brazil (Confalonieri et al., 2007). Reduced water and food availability and air pollution from forest fires led to increased health risks requiring governmental financial aid.

Climate change may influence the future occurrence of drought. There is high confidence in projections of increased precipitation variability that could in turn increase the risk of droughts across many regions (Kundzewicz et al., 2007). Observations have shown an increase in the severity and duration of droughts over larger areas since the 1970s (IPCC, 2007). More intense and multi annual droughts have also been observed in some semi-arid and sub-humid regions, including Australia, the Sahel, Southern Canada and Western USA (Kundzewicz et al., 2007). This suggests a particular vulnerability in these regions to any projected increases in drought occurrence. It is considered likely that the extent of drought affected areas will increase in the future with climate change (Kundzewicz et al., 2007). Temperature is projected to increase everywhere. Global mean precipitation is projected to increase with current models showing a projected decrease in precipitation in sub tropical regions and increases at

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high latitudes and in the tropics (Kundzewicz et al., 2007), however there is greater uncertainty associated with projections of precipitation than those for temperature (Meehl et al., 2007). Evaporative demand is also likely to increase everywhere. Drought is not solely affected by climatic drivers, non-climatic drivers such as population changes, land use and water management have a large influence on water availability and hence drought (Kundzewicz et al., 2007). As these will almost certainly change in the future they need to be accounted for to gain a complete understanding of future drought events and their impacts.

Improving an understanding of the sources of uncertainty in the water-climate interface was identified as a research priority in recent Intergovernmental Panel on Climate Change (IPCC) reports (Kundzewicz et al., 2007; Bates et al., 2008). It is widely acknowledged that model projections of future climate change contain uncertainty due to three distinct sources; internal variability (or natural variability), modelling uncertainty and emissions uncertainty (Hawkins and Sutton, 2009). Internal variability has been shown to be the dominant source of uncertainty on short-term, decadal timescales, whilst modelling uncertainty has a larger influence on longer term projections (toward the end of the century). Emissions uncertainty becomes increasingly important after a lead time of approximately forty years. The total uncertainty increases with time (Hawkins and Sutton, 2009). In this study we include modelling and emissions uncertainty through the use of a perturbed parameter ensemble of the HadCM3C Earth system model (Lambert et al., 2012) and two future emissions scenarios as detailed in Sect. 2. Internal variability is not assessed in this study.

Additional uncertainties arise during impacts assessments related to the impact itself. In the case of drought, uncertainties are often associated with the choices around how a drought is defined. This includes the type of drought (for example meteorological, hydrological or agricultural), and the severity, duration, location and frequency of the drought.

There are many different drought indices available, reflecting the different aspects of the hydrological cycle. Three are considered here: the Standardised Precipitation Index

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(SPI) gives an indication of meteorological drought, the Soil Moisture Anomaly (SMA) sits somewhere between meteorological and hydrological drought and can be used as an indicator of agricultural drought, and the widely used Palmer Drought Severity Index (PDSI), which provides a measure of soil moisture and is also considered to be an indicator of agricultural drought. The choice of threshold below which a drought is measured reflects drought severity and may influence the interpretation of future drought projections. To address this we have calculated the time spent in drought below five different thresholds.

Any assessment of future projections of drought and their associated impacts involves many choices and uncertainties. This analysis aims to better understand which choices are more important in terms of the future uncertainty and which ones have less influence. An informed inclusion of uncertainties in future projections of drought can help to ensure that response options are designed to be robust to the range of potential futures.

The results are analysed to examine whether there is a change in the proportion of time spent in drought in the 2080s relative to the baseline period. Where there are significant differences, we assess the percent of the land surface with either an increase or decrease in the time spent in drought for the different thresholds, indices, future scenarios and climate model ensemble members. We then compare the contribution of each source of uncertainty by calculating the variance across each source. Collating the sources of uncertainty in this way provides a means to assess how the different sources affect future projections of drought, whether certain sources of uncertainty dominate and where uncertainty is less, resulting in more robust messages.

2 Climate model simulations

In this study we use a large ensemble of climate change simulations with different configurations of HadCM3C (Booth et al., 2012b), a coupled atmosphere-ocean-carbon cycle Earth system model. The model is configured from HadCM3 (Gordon et al.,

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2000), a widely-studied coupled ocean-atmosphere model used by the Hadley Centre to provide input for the IPCC Third and Fourth Assessment Reports. In the HadCM3C configuration, the model incorporates a fully interactive (land and ocean) carbon cycle with dynamic vegetation and an interactive sulphur cycle scheme, in addition to the standard physical representations of the atmosphere, ocean and land surface. Flux adjustments are used to restrict historical simulation biases in sea surface temperature and salinity, following Collins et al. (2011). The design and setup of this Earth System Ensemble (ESE) is fully described by Lambert et al. (2012).

The ESE is a development of a series of previously investigated perturbed parameter ensemble (PPE) experiments (e.g. Murphy et al., 2009; Collins et al., 2011; Booth et al., 2012a), which investigated the uncertainties associated with different aspects of the climate system. The ESE brings together these ensembles to simultaneously explore parametric uncertainty in the atmosphere, ocean, land carbon cycle and sulphur cycle processes in this Earth system model. An ensemble of 57 members has been created and driven using two future emissions scenarios; the IPCC Special Report on Emissions Scenarios (SRES) A1B scenario (Nakicenovic et al., 2000), a "business as usual" emissions scenario, and Representative Concentration Pathway 2.6 (RCP2.6; Moss et al., 2010), an aggressive mitigation scenario. The simulations also include appropriate historical periods. Comparison of these scenarios allows us to understand what changes and climate impacts might be mitigated by a change in behaviour, and also how much climate change we are already committed to because of the delayed response of the Earth system.

The ESE is the first experiment of its kind, and allows the effects of interactions between uncertainties in the different components to be systematically explored. Table 1 illustrates the range of projections given by the ESE for the end of the century for temperature, precipitation and CO_2 concentration. In Lambert et al. (2012) it is shown that interactions between uncertainties play a significant role in determining the spread of responses in global mean surface temperature. The ESE also explores a wide range of regional response, and therefore provides a useful resource for the provision of

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regional climate projections and associated uncertainties. It is important however to note that the ensemble was designed to sample a large range of uncertainty, rather than to produce a set of equally plausible projections. It is more appropriate therefore to interpret the ESE projections as a spread of possible outcomes, rather than a set of likely futures.

3 Methods

3.1 Application of drought indices

Three indices of drought are calculated and analysed, the Standardised Precipitation Index (SPI), the Soil Moisture Anomaly (SMA) and the Palmer Drought Severity Index (PDSI), based on the approach of Burke and Brown (2008). Details of each of these indices and their application in the present study are provided below.

3.1.1 Standardised Precipitation Index (SPI)

The SPI was developed by McKee et al. (1993) and has recently been adopted as the standard meteorological drought index by the World Meteorological Organisation (WMO) (Sheffield and Wood, 2011). It is based on the probability of precipitation for a particular location (Keyantash and Dracup, 2002) where observed or modelled precipitation is calculated as a deviation from the longer term normal (Sheffield and Wood, 2011). The index can be applied to multiple timescales of accumulation, typically ranging from one to 48 months. This represents the way that the impacts of reduced precipitation vary with event duration (Sivakumar et al., 2010).

The present study uses a twelve month accumulation period. Because the SPI is based solely on precipitation, which is readily available from both observed and modelled data, and is relatively simple to calculate, it is widely applicable for drought assessment (Sivakumar et al., 2010). This is particularly true for developing countries where data may be limited. This drought index is only really applicable to

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meteorological drought as it only includes precipitation and does not account for interactions with the land surface or temperature.

For this study, the SPI is calculated from climate model monthly precipitation that was normalised around the baseline thirty year distributions for each model grid square.

3.1.2 Soil Moisture Anomaly (SMA)

The SMA is a useful index of agricultural drought as it reflects the moisture available for plant usage. The available soil moisture, calculated within a Global Circulation Model (GCM), is a crucial component of the hydrological cycle that essentially involves a balance between precipitation, runoff, and evaporation (including evapotranspiration by vegetation; Sheffield et al., 2009). Although the SMA is not widely used as an operational drought index because observations of soil moisture are not routinely collected, it can provide a good indication of modelled agricultural drought. It also has the advantage of being calculated within the coupled climate model so will inherently include CO_2 physiological effects if these are included in the climate model and the effect of any included feedbacks on climate projections.

For this study the SMA is calculated from the direct model output of soil moisture using the approach of Burke and Brown (2008). Soil moisture anomalies are calculated for the top 1 m of soil, using data for the first three soil layers in the HadCM3C model, having thicknesses from the top of 0.1, 0.25 and 0.65 m respectively.

3.1.3 Palmer Drought Severity Index (PDSI)

The PDSI has been referred to as an index of meteorological drought (Keyantash and Dracup, 2002). It has also been used as an index of agricultural drought and is one of the most widely used operational drought indices (Sheffield and Wood, 2011). It was first developed by Palmer (1965), based on limited data from the United States to give a measure of the "cumulative departure of moisture supply" (Keyantash and Dracup, 2002). Based on the water balance equation for a particular location (Sivakumar et al.,

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2010) the PDSI is essentially a balance between incoming and outgoing water using a two layer, bucket type scheme with climatological calibrations for a specific location in space and time (Burke et al., 2006). Like the SPI, the PDSI values are dimensionless and generally range between +4 and −4 with any value below zero being indicative of water shortage (Keyantash and Dracup, 2002).

The PDSI is particularly sensitive to changes in temperature because of the rather simplistic representation of potential evaporation that is commonly used (Sheffield and Wood, 2011). This means that observed and projected global temperature increases due to climate change may result in a much stronger increase in drought than is considered physically plausible. The Penman-Monteith potential evaporation model is an alternative approach to calculating potential evaporation that is considered more physically plausible than the Thornthwaite model (van der Schrier et al., 2011). However it does not necessarily reduce the strong temperature sensitivity of the PDSI significantly (van der Schrier et al., 2011).

Several other aspects of the PDSI have been criticised, including the lack of spatial consistency (Sheffield and Wood, 2011), the limited representation of vegetation and roots, an inability to account for frozen processes (Burke et al., 2006), the underestimation of runoff, and the simplification of soil moisture across regions (Sivakumar et al., 2010).

In this study the self calibrated PDSI is used. This was developed in 2004 (Wells et al., 2004) to improve the ability to make spatial comparisons as the calibrations are based on local conditions rather than the fixed values of the original PDSI (Dai, 2011). The calculation of the PDSI is relatively complex and requires monthly data for precipitation, temperature, the available water holding capacity of the soil, and potential evaporation (calculated from temperature, relative humidity, pressure, wind and short and long wave radiation). Potential evaporation is calculated using the Penman–Monteith equation following the methodology of Burke et al. (2006) as this is more suitable for application to climate change scenarios.

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3.1.4 Drought thresholds

To assess the influence of drought severity on projections of future drought occurrence, specific thresholds (severities) of drought are analysed to give the proportion of time spent in drought. For example a 20th percentile drought may have minimal projected change whilst the more extreme 10th percentile drought may change significantly if the shape of the distribution changes in the future (see Fig. 1). This means that focussing on only one level of drought severity may not include important potential changes at other severity levels. This approach provides common values to aid comparison across all three indices. Drought severity is defined as the 1st, 5th, 10th, 15th, and 20th percentiles of the baseline distribution for each drought index and each model grid square, following the methodology of Burke and Brown (2008). The proportion of time spent in drought (e.g. below the 10th percentile of the baseline distribution) is then calculated for the baseline period 1961–1990 and the 2080s (2070 to 2099). The actual index value for each of the assessed percentiles of the baseline distribution is used as a threshold for future time periods and the number of months below the threshold in every year is calculated for each 30 yr time period. This is then converted into a proportion of time over the thirty years spent in drought for each drought threshold.

3.2 Analysis

Analysis and communication of results from a large ensemble, as used here, presents certain challenges. Rather than presenting ensemble mean projections, here we provide an alternative presentation based around a typical "exemplar" member of the ensemble. The concept of model consensus (Kaye et al., 2012; McSweeney and Jones, 2012) is also used to analyse the degree of agreement across the different model projections. Unlike the ensemble mean, a representative exemplar model projection provides joint patterns of climate response for several climate variables that corresponds to a physically consistent solution to the modelled representation of climate system processes. Variability is also retained in the exemplar, which is important for realistic climate impact studies. This approach enables the same model to be traced across the three drought indices, different drought thresholds and significant increases and decreases whilst maintaining the model's spatial characteristics.

The exemplar member was chosen on the basis that, on average, across selected regions and variables, it possesses the median response of the ensemble. Specifically, for a selection of 24 countries, including the nineteen G20 nations (Vestergaard, 2011) and five others, the ESE members are ranked for each of the four seasons by their projected temperature and percentage precipitation change at the end of the 21st century in response to the A1B emissions scenario. These ranks, normalized by the number of runs so that 0.0 corresponds to coldest/driest, 1.0 to hottest/wettest, and 0.5 to the median, were then averaged to give an average rank for each member, assuming equal weight for each country. In Fig. 2, a scatter plot of the average rank and the global temperature response is shown for the ESE members. Not surprisingly, a strong relationship between these two quantities is obtained. Several members lie close to the median. The exemplar member is chosen in preference to other similarly ranked candidates on the basis that it possesses a small variance in rank. Country responses are used here to select the exemplar since detailed climate projections for these countries, based on the ESE models that comprehensively sample earth system modelling uncertainty, will shortly be produced. It is worth noting that although on average the selected member is close to the median, this does not preclude that for some regions and variables, the exemplar can be far from the median.

For each ensemble member, future scenario, drought metric and threshold we analyse future projections of the proportion of time spent in drought in the period 2070–2099 (representative of the 2080s) compared to the baseline period 1961–1990. The annual proportion of time spent in drought for the baseline and the 2080s is calculated in each case and for each model grid cell.

To test whether there is a significant difference between the two time periods, a Wilcoxon-Mann-Whitney test is applied (Wilks, 2006). This is a non-parametric statistical test with the null hypothesis that two data samples are drawn from the same

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distribution. The underlying principle of the Wilcoxon-Mann-Whitney test is exchangeability; if the two samples of data from the baseline and the 2080s are not different, then each data point is as likely to be from the baseline period as the 2080s. The test statistic pools the data, ranks it and sums the ranks from each time period separately. If the sums of the ranks in the two time periods are sufficiently different in magnitude, the null hypothesis is rejected and the two are deemed to be significantly different. In this case a two-sided alternative hypothesis is applied (i.e. the difference between the two time periods could be positive or negative) and the test applied at the 5 % probability level.

Cold regions are excluded from our analysis for all three drought metrics as described by Burke and Brown (2008). Following the approach of Deichmann and Eklundh (1991), global cold regions are defined as grid cells where the temperature is less than 0 °C for more than six months of the year and where less than three months of the year have temperatures greater than 6 °C. We use the mean of the thirty year average temperature for the 1961–1990 baseline, averaged across ensemble members of the A1B scenario, as the basis for these calculations. Although in practice, each model ensemble member would have a unique cold region using the above definition, for internal consistency we use a standard region for all calculations.

To summarise this information over the whole ensemble we use a consensus mapping approach (Kaye et al., 2012). We calculate and map the proportion of ensemble members that exhibit a significant increase, decrease, or no significant change in proportion of time spent in drought (McSweeney and Jones, 2012; Knutti et al., 2010). This provides a measure of agreement on the signal of change (or no change) for different regions around the world and across the ensemble.

In order to compare the influence of the different ensemble members, future scenarios, drought metrics and thresholds on projections of future drought, the proportion of the land surface with a significant increase or decrease in time spent in drought is calculated for each. This provides a means of qualitatively comparing the different future projections of drought and the influence of different sources of uncertainty on

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the projections. The contribution of each source of uncertainty to the overall included uncertainty is calculated based on an adaptation of the approach of Hawkins and Sutton (2009). We calculate the variance of each uncertainty source and then compare the mean of each resultant variance.

4 Results

Here we present our results for the proportion of time spent in drought for the three drought indices, two emissions scenarios, five drought thresholds and fifty seven ensemble members analysed. We first outline how key climate variables are projected to change by the end of the 21st century, both spatially and temporally, to illustrate some of the driving processes behind changes in drought occurrence. We then present the significant changes in time spent in drought in the 2080s compared to the baseline period for both future scenarios, followed by a comparison of the four uncertainties considered in this study.

4.1 Climatic variables

Both temperature and precipitation influence the processes leading to drought events. Understanding how these variables are projected to change can increase our understanding of the processes involved in the projected changes in drought indices. In Fig. 3 we therefore present changes in annual mean land surface air temperature, and percentage change in annual mean land precipitation for the two future scenarios. Figure 4 shows the spatial variation in the change in these two quantities for the exemplar simulation. Both figures are presented for the same area of the land surface as the drought indices, i.e. cold regions are excluded as defined in Sect. 3.2.

Both future scenarios show a similar projected increase in global average land temperature until the 2040s. After this time, temperatures for the RCP2.6 scenario stabilise, while for the A1B scenario a continued increase is projected. The range of projected

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temperature changes across the model ensemble is much larger for the A1B scenario than for the RCP2.6 scenario. Projections for the percentage change in global average land precipitation also show an increase by the end of the century for both emissions scenarios, although the projected change does span zero. The RCP2.6 scenario gives a narrower range of precipitation increases by the end of the century than the A1B scenario ensemble and lies completely within the range of the A1B scenario.

Whilst temperature is projected to increase everywhere by the end of the century, there are marked regional differences in the magnitude of change as shown in Fig. 4 for the exemplar. Greater warming is projected over the Northern Hemisphere, particularly at higher latitudes for the A1B emissions scenario. Projections of precipitation also show clear regional patterns. Drying is projected in Southern Europe, the Mediterranean, Northern Africa, Southern Africa, Central America, across the Amazon, Chile, and Southern and Eastern Australia, whilst wetting is projected for all other regions.

4.2 Significant changes in time spent in drought

Future projections of drought in the 2080s for the exemplar model and the ensemble consensus are shown in Fig. 5 for the A1B scenario and Fig. 6 for the RCP2.6 scenario for each of the three drought indices. Using the significance testing described in Sect. 3.2, maps of the proportion of ensemble members that exhibit a significant increase, decrease or no significant change in the proportion of time spent in drought are shown in the right column of both figures. The proportion of models agreeing on a significant decrease, no significant change or a significant increase in drought is indicated by shading (the darker the shade the greater the agreement). White represents areas where less than 50 % of models agree (Kaye et al., 2012).

For the A1B emissions scenario there are clear differences in drought projections between drought indices, both spatially and in terms of magnitude and direction of the projected change. More models agree on significant increases for PDSI drought, whilst projections of SPI drought show the least model agreement across the ESE model ensemble for significant increases. For some regions there is a consistent signal across

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all three drought indices for both significant increases and decreases in time spent in drought. For instance, significant increases in time spent in drought in the 2080s are projected for Central America, the Amazon, Southern Chile, the Mediterranean, North-Western Africa and parts of South Africa for all three drought indices. In general, projections of PDSI drought have stronger model agreement and a larger spatial extent across those regions. Significant decreases are projected for Northern India, parts of Central Asia and parts of East Africa for all three drought indices, with the SPI showing the largest area with significant decreases in time spent in drought.

A contrasting signal between indices is apparent in projections for some regions; for example the SPI indicates significant projected decreases in time spent in drought for Northern Canada, Northern Europe and Northern Asia, while the PDSI and SMA predominantly show significant increases in those regions. This broadly coincides with regions that are projected to experience future increases in precipitation (Fig. 4) which is directly reflected in the SPI, as it is based solely on precipitation. The patterns of projected temperature changes (Fig. 4) suggest that temperature changes in these regions may have a greater influence on drought projections using the SMA and PDSI than precipitation changes.

Projections for some regions show no significant change in the time spent in drought in the future. This is because the increases or decreases in time spent in drought given by the drought indices are not different enough from the baseline to be categorised as significant in this study. More areas of the globe show no significant change in time spent in drought for the SPI projections than for the other two drought indices. In some cases, regions with no significant change correspond to regions with lower model agreement for precipitation changes. However, the precipitation projections shown are for all changes rather than just those that are significantly different from the baseline.

Figure 5 (left) shows the proportion of time spent in drought in the 2080s for each model grid square for the A1B exemplar model simulation (excluding the cold regions). For the 10th percentile drought (as shown here) values greater than 0.1 indicate an increase in time spent in drought compared to the baseline and values below 0.1 indicate

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a decrease. Similar regional patterns of change to the significance plots are evident, particularly for the strongest increases in time spent in drought. These plots illustrate the change in the proportion of time spent in drought across the entire globe rather than just where the change is significant (as the model agreement plots do) so they include the projected changes for this ensemble member for regions that show no significant change across the model ensemble. For the exemplar model ensemble member, the regions corresponding to no significant change in the model agreement plots (Fig. 5, right) mainly show decreases in time spent in drought in the future.

Projections for the RCP2.6 scenario are regionally similar to those for the A1B scenario, although with less model agreement, smaller magnitude of change and a smaller area showing significant change (see Fig. 6).

4.3 Comparing uncertainties in future drought projections

We compare the four included sources of uncertainty by calculating the percentages of the land surface (excluding cold regions) with a significant increase and decrease in the time spent in drought in the 2080s (as defined in Sect. 3.1). These are shown in Fig. 7.

Of the three drought indices, PDSI drought shows the largest proportion of the land surface with a significant increase in drought (approximately 60 % for the A1B scenario and between 50 %–60 % for the RCP2.6 scenario) and the smallest proportion with a significant decrease (Fig. 7). SPI drought shows the lowest percentage of the land surface with a significant increase in time spent in drought (between 10 %–20 % for the A1B scenario and 5 %–20 % for the RCP2.6 scenario) and the smallest significant increase with values ranging between 15 %–50 % for the A1B scenario and slightly smaller increases for the RCP2.6 scenario. As Fig. 5 shows, in some regions SPI projections show significant decreases in time spent in drought whilst the SMA and PDSI projections show significant increases. This would explain the lower percentage of the land surface with a significant increase for SPI and the higher significant decreases found with the SPI (as in Fig. 7). Since the SPI is based solely on precipitation

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the difference in behaviour appears to be linked to future precipitation projections in those regions. Projections for SMA drought lie mostly in between the other two drought indices with between 20 % and 50 % of the land surface projected to experience a significant increase in the time spent in drought under the A1B scenario and between 15 % and 40 % under the RCP2.6 scenario. Projections of both SMA and PDSI drought indicate that more of the land surface could have a significant increase in time spent in drought in the 2080s than a significant decrease.

The spread across the ensemble (modelling uncertainty) varies with drought index, future scenario and to a lesser extent, drought threshold. The smallest ensemble spread is found for significant decreases in PDSI drought and the largest ensemble spread occurs with significant increases in PDSI drought. Figures 5 and 6 show that for the PDSI, significant increases cover larger areas of the globe than the other two drought indices and significant decreases cover less. The ensemble members show different behaviour across the drought indices and for significant increases and decreases in time spent in drought.

In all cases the projections for the two future scenarios overlap to varying degrees. The least overlap occurs in the projections of significant increases in PDSI drought. As Fig. 5 shows, under the A1B scenario large areas of the globe have significant increases for PDSI, whilst under the RCP2.6 scenario, there are more areas with no significant change. As PDSI is influenced by temperature, this appears to be related to the higher temperature changes projected under the A1B scenario (Fig. 4). For both future scenarios the projections of significant decreases in SPI and PDSI drought almost completely overlap. Broadly speaking, the spatial patterns of the two emissions scenarios are similar, as shown in Figs. 5 and 6, with the RCP2.6 scenario having less grid squares with significant changes and less model agreement where they do occur. The magnitude of change is therefore lower for RCP2.6 even if that change occurs over roughly the same number of grid squares as it does for the A1B scenario.

There are generally minimal trends across the different drought thresholds for significant increases in time spent in drought for all three drought indices. A positive trend is

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apparent for significant decreases in SPI drought. The general geographical patterns of change evident in Figs. 5 and 6 for the 10th percentile are similar across the other four percentiles with the main differences being in magnitude of model agreement and an expansion of areas with a significant decrease in time spent in drought for the 15th and 20th percentiles. The underlying regional patterns of change are not strongly influenced by choice of drought threshold.

The dominant source of uncertainty in this study is the choice of drought index (see Fig. 8), across both time periods and both increases and decreases in time spent in drought (drought index uncertainty accounts for between 60 %–85 % of the total included uncertainty). Modelling parameter uncertainty ranges from 9 %–17 % and is larger for decreases in time spent in drought than increases. The influence of future scenario on the total included uncertainty increases with time and is larger than parameter uncertainty in the 2080s (from 5 %–6 % in the 2050s to 17 %–18 % in the 2080s). Choice of drought threshold has minimal influence on the proportion of the land surface with a significant increase in time spent in drought (0.4 %) and a small influence on significant decreases (6 %–7 %). Overall there is larger variance for increases in time spent in drought than decreases, and for the 2080s relative to the 2050s (Fig. 8, left).

5 Discussion

5.1 Drought indices

We find considerable differences in future projections of time spent in drought between the three drought indices used in this study, the SPI, SMA and PDSI. The many drought indices that have been developed tend to represent different components of the hydrological cycle and types of drought that can occur (Sivakumar et al., 2010; Keyantash and Dracup, 2002; Sheffield and Wood, 2011). Different drought indices have been shown to give a range of outcomes of drought occurrence. For example Burke and Brown (2008) compared several drought indices projections of the change in percent

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area of the land surface under a doubling of CO_2 in moderate drought and found that the SPI gave changes ranging from −5 % to 10 %, the PDSI gave changes from 10 % to 35 %, and the SMA gave changes from 5 % to 20 % approximately. This may be related to the aspect of the hydrological cycle that they represent, or the strengths and weaknesses of the formulation of the index itself (as detailed in Table 2). Resultant differences in three drought metrics, time series of precipitation, soil moisture, and the PDSI, have previously been shown to be related to the climatic variables upon which they are based, particularly precipitation and temperature (Burke, 2011). Burke (2011) showed that all three metrics were similarly sensitive to precipitation, whilst the response to changes in temperature was metric dependant. The PDSI was the most influenced by changes in temperature, soil moisture to a lesser extent and precipitation was shown to be independent of temperature changes. Whilst the current study uses the SPI rather than a time series of precipitation directly from the model, our results largely agree with these findings.

Regions with a strong decrease in precipitation are projected to experience increases in time spent in drought for all three drought indices, whereas regions with strong projected increases in temperature tend to give divergent results across the drought indices. This is particularly the case for the SPI, which depends solely on regional precipitation, for which projected changes are generally more uncertain than those for temperature, as are those for soil moisture (Falloon et al., 2011). Contrastingly, projections of PDSI drought, which are largely influenced by temperature changes, show large areas of the globe with a significant increase in drought. The reduced uncertainty associated with temperature projections results in reduced uncertainty in PDSI drought projections.

Soil moisture is strongly linked to vegetation and land use change. In vegetated regions, increased atmospheric CO_2 concentrations may fertilise plant growth and influence changes in soil moisture. Increasing CO_2 has been shown to contribute to reductions in soil moisture drought, since decreased stomatal opening may lead to less moisture being lost to the atmosphere through evapotranspiration (Betts et al., 2007;

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Gedney et al., 2006). We have not attempted to separate vegetation changes or CO_2 physiological effects (other than what is implicit in the climate model) in the drought calculations in this study and they may contribute to some of the differences between the SMA and the other two drought indices. HadCM3C also did not explicitly model crops or agriculture, which respond differently compared to the generic grasses that were modelled.

Our study suggests that the choice of drought index can influence the outcome of a climate change impacts assessment of drought and that using only one index may not accurately represent the range of possible drought futures.

5.2 Climate modelling uncertainty

The HadCM3C Earth System Ensemble model experiment was designed to sample a wide range of uncertainties, including effective climate sensitivity, which ranges between 2.2–5.5 °C (Collins et al., 2011), and climate carbon feedback strength (Booth et al., 2012b). This means that the ensemble members give a wide range of projected global temperature changes by the end of the century (Fig. 3a). It has been shown that the PDSI is particularly influenced by temperature changes (Burke, 2011) and our results show that the ensemble spread is greatest for significant increases in time spent in PDSI drought (see Fig. 7), reflecting the range of projected temperature changes. Conversely, significant decreases in PDSI drought have the narrowest range across the ensemble. Model projections of temperature driven drought decreases (i.e. the PDSI) have the smallest spread since all ensemble members give a projected future increase in temperature.

The soil moisture anomaly is the only drought index that will be directly influenced by perturbations in CO_2 concentrations and resultant impacts on vegetation fertilisation and runoff, since it is calculated directly from model output that included the MOSES2 land surface scheme. Unlike previous studies of soil moisture and runoff (Burke, 2011; Betts et al., 2007) the model simulations applied here do not use a switch for CO_2 physiological effects. Instead, a spectrum of CO_2 physiological effects is applied (Booth

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et al., 2012b) resulting in each ensemble member having a slightly different impact. This could explain differences between the SMA and the SPI, and would influence the ensemble range for SMA only. For instance, a recent study which used an ensemble of HadCM3 that contained a "switch" for CO_2 fertilisation showed that the effect of carbon dioxide increased available water and was of a similar order of magnitude as the climate change effect (Wiltshire et al., 2012).

5.3 Future scenarios uncertainty

We have used two future scenarios in this study arising from different scenario methodologies. They do not attempt to span the range of uncertainty due to future emissions so the range of future scenario uncertainty is likely to be larger than that shown here. As the two future scenarios used in this study, A1B and RCP2.6, were developed through separate processes they are not necessarily directly comparable. A1B is an SRES scenario that represents a medium to high emissions scenario and is not the highest of the SRES (Nakicenovic et al., 2000). RCP2.6 is an aggressive mitigation scenario (Moss et al., 2010) that was developed for the IPCC's Fifth Assessment Report and has lower emissions than those considered in the IPCC Fourth Assessment Report. It is intended to be indicative of a possible "lower limit" of climate change if global emissions cuts were to be implemented in the next few years.

Despite the different development methodology, the regional patterns of change in time spent in drought given by both scenarios are very similar, because the model structure is the same, with the main differences relating to magnitude and spatial extent of a projected change. Similar trends between emissions scenario were also noted by Falloon et al. (2012) in vegetation changes from their HadCM3C simulations under the A1B scenario and a mitigation scenario. A comparison of the two scenarios applied in our study illustrates the potential effect of mitigation strategies, as the projected changes for time spent in drought under RCP2.6 are not as strong as those projected under the A1B scenario (in terms of both an increase and decrease in time spent in drought, see Figs. 5 and 6). There was also a greater difference between the scenarios

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for significant increases than decreases in time spent in drought for all three drought indices. In general, significant increases will be more influenced by the projected increases in temperature for the end of the century, which differs considerably between the two scenarios (see Fig. 3), whereas decreases are more likely to be driven by changes in precipitation, as discussed in Sect. 5.1. More of the land surface has a significant increase in the time spent in drought under the A1B scenario, for all three drought indices, than the RCP2.6 scenario. The two scenarios generally give more similar outcomes for significant decreases in the time spent in drought (see Fig. 7). The greatest difference in future drought projections between future scenarios is given by the PDSI metric, which is driven mainly by temperature.

Some regions show opposing precipitation signals between the future scenarios, for example Texas and South-Eastern Europe show a drying under A1B and a wetting under RCP2.6, reflected in projections of SPI drought for those areas. It would be useful to understand the climatic processes leading to these projected changes to understand more fully how mitigation actions may influence drought occurrence regionally.

5.4 Drought thresholds

Our results show very little effect of drought thresholds on the proportion of time spent in drought, in comparison to the other sources of uncertainty that we have assessed. Burke et al. (2006) used HadCM3 simulations to look at three thresholds of PDSI drought, the 1st, 5th and 20th percentiles of current day drought and found that by the end of the century the 20th percentile resulted in approximately 40 % of the land surface being in drought, the 5th percentile gave approximately 25 % and the 1st percentile gave approximately 20 % of the land surface in drought. Our results give a larger proportion of land surface in drought for all thresholds in the 2080s, reflecting the model experiment that has been used. The general regional patterns are similar across thresholds, varying in magnitude as expected. The percent of the land surface with a significant increase in time spent in drought is minimally influenced by choice of drought threshold. Significant decreases indicate some trends across thresholds,

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particularly for SPI drought, with higher thresholds giving a larger percent of the land surface with a significant decrease in time spent in drought. Significant decreases in PDSI drought give a slightly larger ensemble spread for higher thresholds, potentially suggesting a change in the shape of the distribution. This suggests that choice of drought threshold is of less importance when conducting impacts assessments of changes in future drought.

5.5 Dominant source of uncertainty

We have assessed four potential sources of uncertainty in future projections of drought. This analysis suggests that, of the included sources of uncertainty, choice of drought index has the largest influence on the range of drought projections (Fig. 8). Differences between drought indices are widely acknowledged (Sheffield and Wood, 2011; Sivakumar et al., 2010) and discussed above (Sect. 5.1). In all cases the variance due to drought index uncertainty accounts for more than 55 % of the total included uncertainty and is clearly dominant. Of the three remaining uncertainty sources, drought threshold makes the smallest contribution to the total included variance. Modelling parameter uncertainty is an important source of uncertainty in these drought projections, accounting for between 9 %–17 % of the total included variance. The model experiment used for this study was specifically designed to sample a wide range of uncertainty. The use of a perturbed parameter ensemble means that structural model uncertainty has not been explored. This important source of uncertainty could be included through the use of the CMIP5 ensemble of models. The difference between future scenarios is larger for the 2080s than the 2050s with future scenario uncertainty accounting for between 5 %–6 % in the 2050s and 17 %–18 % in the 2080s. There may be a more apparent influence of emissions scenario if RCP2.6 was compared against the other IPCC AR5 RCPs or a more high-end SRES scenario. A further study could therefore explore more emissions scenarios. The choice of drought threshold for an impacts study is often arbitrary and our results suggest that this decision is of less importance when compared to choice of drought index, models and future scenarios.

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Despite global differences between drought indices, model ensemble members and future scenarios, there are some regions with a consistent signal for either significant increases or significant decreases in time spent in drought. For example, projections over the Amazon, Central America and South Africa show consistent significant increases in time spent in drought in the 2080s, and those over Northern India show consistent decreases. The consistent signal across these regions increases confidence in the projections for these areas. Further investigation focussed on these key regions could provide important detail for impacts studies, particularly the Amazon and Northern India. It would be useful to explore the key processes associated with drought occurrence, such as ENSO behaviour, Monsoons and land use change, to understand how they interact with drought occurrence. More of the land surface is projected to have a significant increase in the time spent in drought in the 2080s than a significant decrease for all three drought indices. This has important implications for drought management planning in the future.

Uncertainty due to internal variability of the climate system has been shown to be an important component of the overall uncertainty, particularly for precipitation, on shorter lead times and at regional scales (Hawkins and Sutton, 2011). Given that precipitation changes are the main driver of drought occurrence, it is reasonable to expect that internal variability would contribute to the total uncertainty in future drought projections, particularly at regional scales and shorter lead times. Internal variability has not been assessed in the current study and inclusion of it may influence the relative contributions of each source of uncertainty. It must be noted that this study used an ensemble based on one climate model and two future scenarios. Other climate models could give different results leading to additional uncertainties not explored here. It may also be that the dominant uncertainty changes with different regions or time scales and so further regional studies are warranted. Interactions between impacts may also affect future drought impacts, for example those between crops, irrigation and climate, as may human factors including adaptation measures (Falloon and Betts, 2010) which were not included in this study.

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6 Conclusions

Drought can have wide ranging consequences on the social, economic and environmental systems upon which society depends. The influence of climate change on future drought occurrence could have important consequences for disaster planning and management.

When assessing the potential impacts of climate change on drought occurrence, many choices are made, including drought definition, drought severity, future emissions and type of climate model upon which to base the assessment. These choices may lead to varying ranges of uncertainty in the resultant projections so it is important to understand the contribution that each source may make to the overall uncertainty. This study shows that there are considerable uncertainties in future projections of drought, from multiple sources. We have included four potential sources of uncertainty but others exist which have not been included, such as natural variability and the uncertainty associated with structurally different climate models. Natural variability has been shown to be an important source of uncertainty, particularly on regional and decadal scales (Hawkins and Sutton, 2011). Of the four sources included in this study, the choice of drought index has the greatest influence on the future projections of time spent in drought, followed by future emissions and modelling uncertainty, whilst choice of drought threshold resulted in small variation in drought outcomes.

It is also possible that other sources of uncertainty, such as internal variability, not included in this study, may have an influence on the overall uncertainty and that the influence of sources of uncertainty may change over time and at different regional scales.

Whilst overall the uncertainties in future drought projections are large, for some regions consistent signals are apparent, increasing confidence in projections of changes in drought for those regions. An increase in time spent in drought in the 2080s is projected across the Amazon, Central America and South Africa whilst a decrease is shown over Northern India. In general, more of the land surface is projected to have

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an increase in time spent in drought than a decrease. This has important implications for future drought management and planning.

Despite these uncertainties, it is essential that informed decisions are still taken and acted upon to minimise or avoid the considerable impacts of drought events. The next stage is to understand how this uncertain information can be used as a basis for such decision making.

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Table 1. The end-of-century range of atmospheric CO_2 concentration (extract from Booth et al., 2012b), temperature and precipitation given by the HadCM3C Earth System Ensemble simulations for the SRES A1B and RCP2.6. CO_2 is the 2099 value in ppm. Temperature (°C) and precipitation (%) are based on the end-of-century 10 yr average (2090–2099) relative to the 1961–1990 average, over global land points.

	A1B			RCP2.6		
	10th	median	90th	10th	median	90th
Atmospheric CO_2 concentration	635	794	972	390	449	514
Land temperature change	4.4	5.7	7.7	2.0	3.0	3.9
Land precipitation change	2.5	5.8	8.2	2.9	4.1	6.5

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Table 2. Summary of the three drought indices applied in this study.

Drought Index	Drought Type	Variables	Advantages	Sensitivities and Caveats
SPI (Standardised Precipitation Index) (McKee et al., 1993)	Meteorological	Precipitation	WMO standard meteorological index; data readily available; relatively simple to calculate; applicable to different timescales	Reflects only precipitation
SMA (Soil Moisture Anomaly) (Burke and Brown, 2008)	Agricultural	Modelled soil moisture	Can be calculated within a climate model so includes feedbacks that are in the model	Minimal observations available so difficult to validate modelled data. Very complex, needs driving data and land surface parameterisation. The HadCM3C model used here does not explicitly represent agricultural areas.
PDSI (Palmer Drought Severity Index) (Wells et al., 2004)	Agricultural and/or meteorological	Precipitation, temperature, available water holding capacity and potential evaporation (calculated with the Penman-Monteith equation)	Includes more than just precipitation; has a measure of antecedent conditions built into the calculation	Sensitive to temperature (potential evaporation calculation) so increases tend to give overestimates of drought; does not account for snow or frozen ground; relatively complex; issues with spatial comparability

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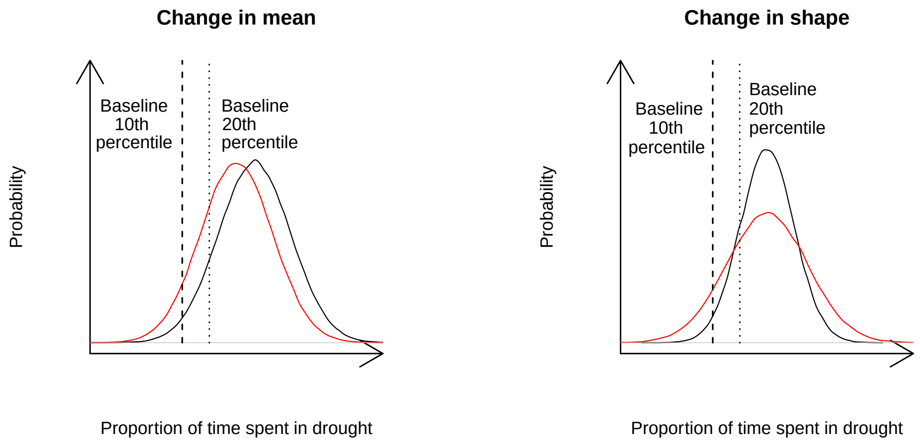

Fig. 1. Schematic of drought threshold. The black line represents a sample baseline distribution and the red line a sample future distribution.

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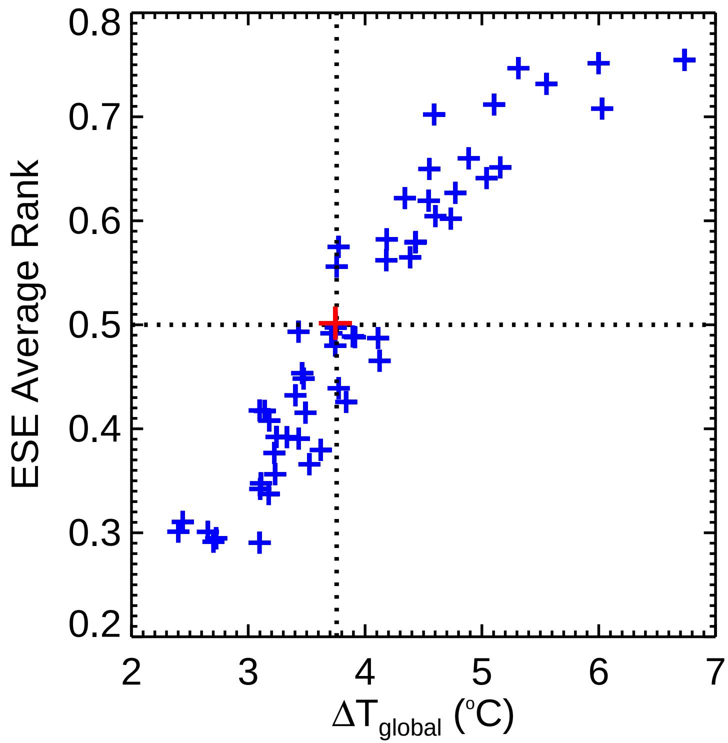

Fig. 2. The Earth System Ensemble members ranked by their A1B end-of-century temperature response and percentage precipitation change, averaged over the four seasons for 24 selected countries as a function of their 2080–2099 annual global temperature response with respect to 1961–1990. The exemplar member selected to show a representative median response is marked in red.

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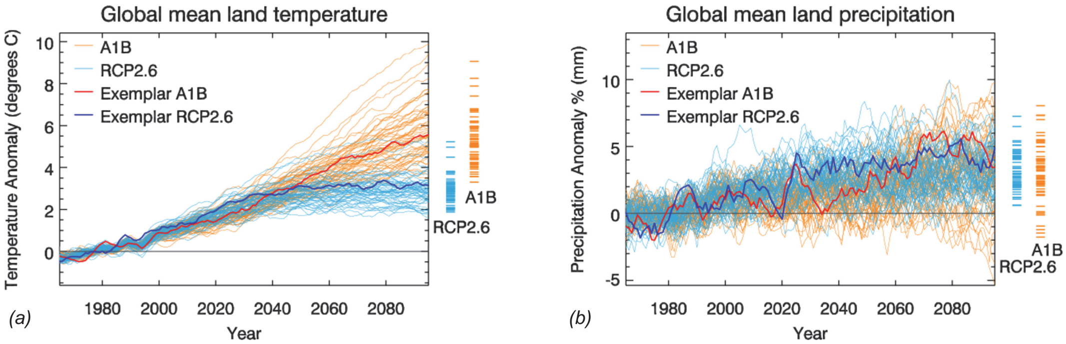

Fig. 3. Annual mean temperature **(a)** and percentage precipitation **(b)** anomalies (with 5 yr smoothing) from 1961 to 2099 (relative to the 1961 to 1990 average) avereaged over land points, excluding cold regions, for the HadCM3C Earth System Ensemble simulations. The A1B future scenario is shown in orange and RCP2.6 is shown in blue (individial lines represent individual models). The two exemplar simulations are shown in red (A1B) and dark blue (RCP2.6), respectively. The range of the ensemble is shown to the right of each plot, with the final 30 yr average (2070–2099) for each ensemble member shown for each future scenario.

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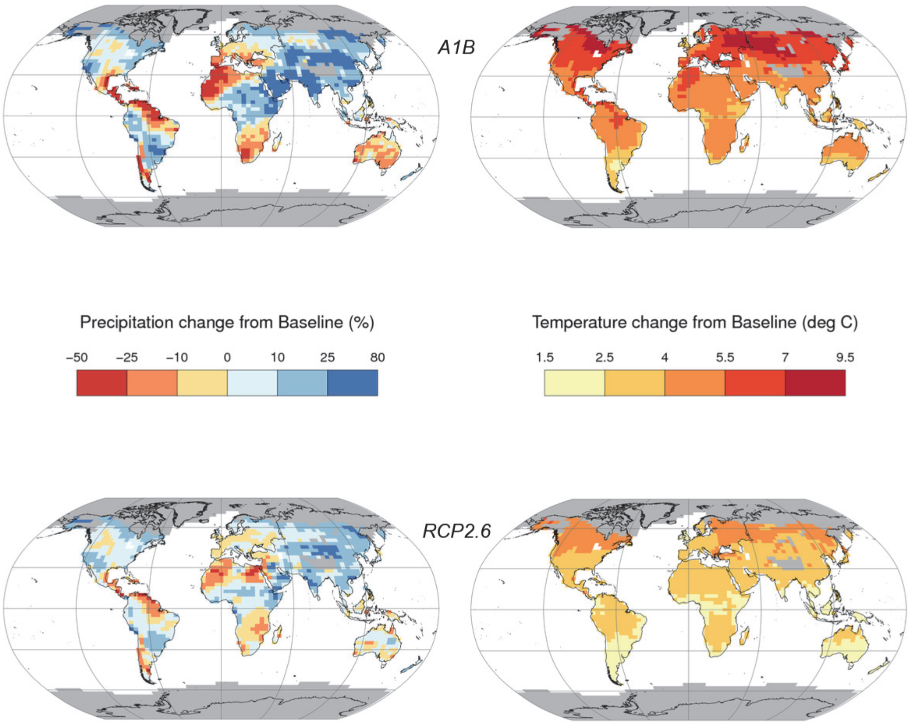

Fig. 4. Precipitation (left) and temperature (right) anomalies for the 2080s (2070–2099) from the baseline 1961–1990 for the exemplar model of the HadCM3C Earth System Ensemble for A1B (top) and RCP2.6 (bottom) future scenarios. Grey regions represent the exluded cold regions.

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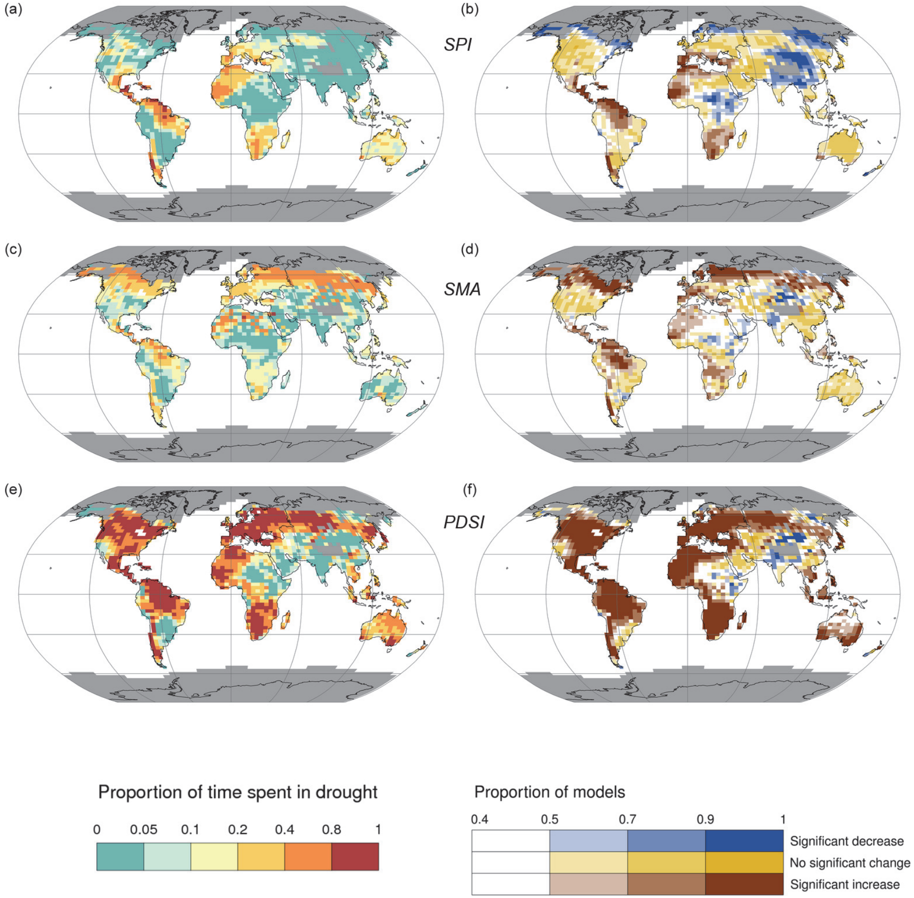

Fig. 5. The proportion of time spent in drought for three drought indices from the HadCM3C Earth System Ensemble for the A1B future scenario in the 2080s (2070–2099), exemplar model (left) and model agreement of significant changes (right). SPI **(a)** and **(b)**, SMA **(c)** and **(d)**, PDSI **(e)** and **(f)**. Grey areas represent the exluded cold regions.

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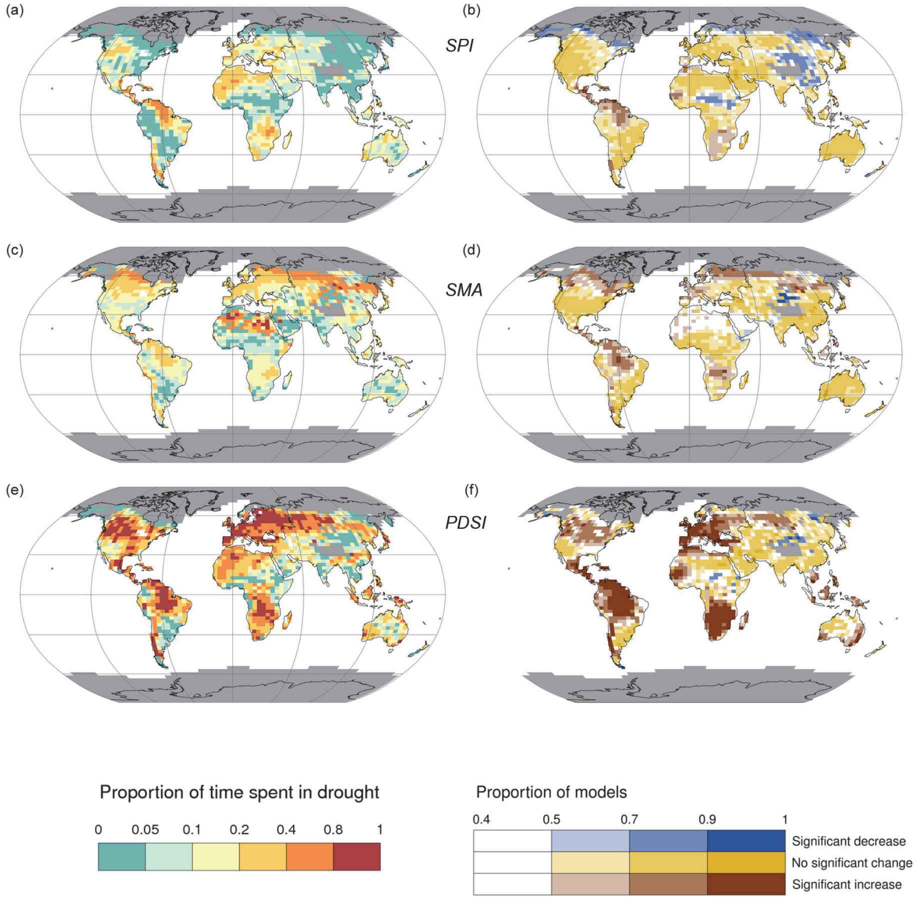

Fig. 6. The proportion of time spent in drought for three drought indices from the HadCM3C Earth System Ensemble for the RCP2.6 future scenario in the 2080s (2070–2099), exemplar model (left) and model agreement of significant changes (right). SPI **(a)** and **(b)**, SMA **(c)** and **(d)**, PDSI **(e)** and **(f)**. Grey areas represent the exluded cold regions.

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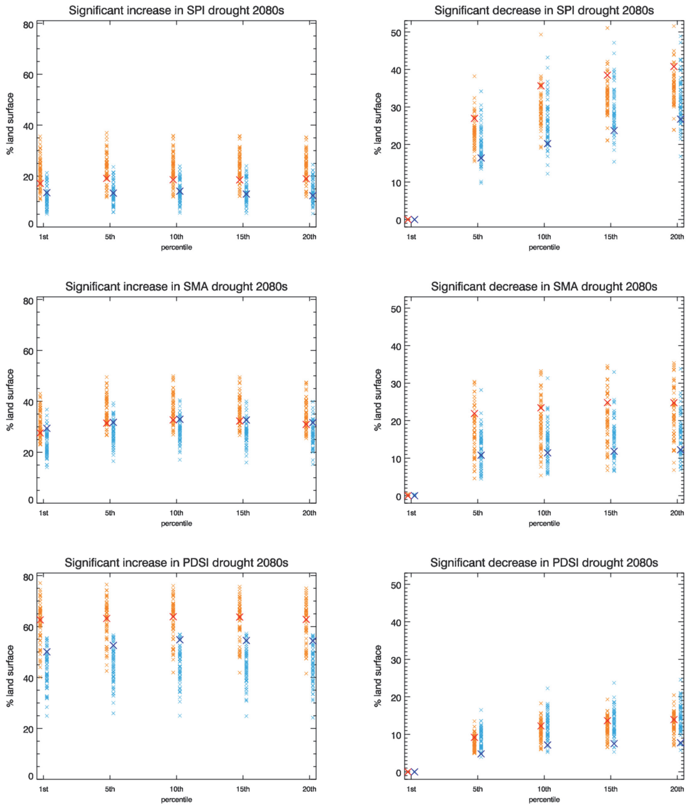

Fig. 7. The percent of the land surface (non-cold areas) with significant changes (as defined in Sect. 3.1) in the time spent in drought in the 2080s (2070–2099) as given by the HadCM3C Earth System Ensemble (increases (left column) and decreases (right column) for the three drought indices (SPI (top row), SMA (middle row) and PDSI (bottom row)). The A1B future scenario is shown in orange and RCP2.6 shown in blue. The crosses represent individual model responses with the exemplar ensemble member marked larger symbols in red (A1B) and dark blue (RCP2.6).

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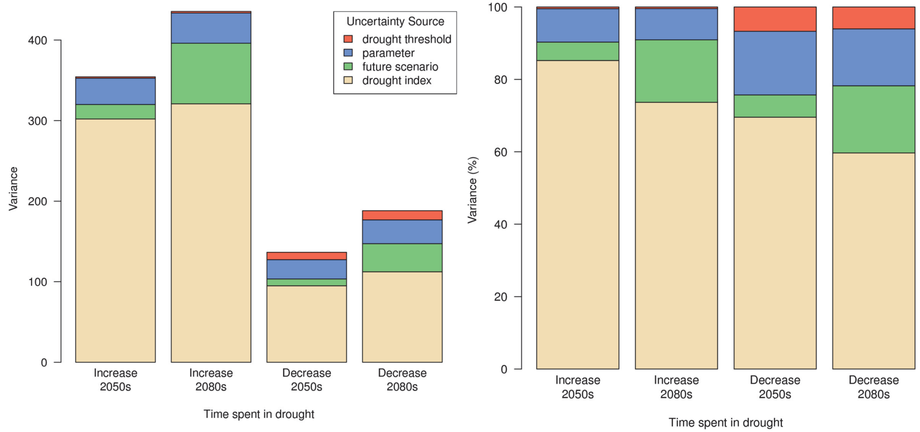

Fig. 8. The variance of each included source of uncertainty, actual variance (left) and as a percentage of the total included variance (right), calculated from the percent of the land surface with a significant increase or decrease in time spent in drought in the 2050s (2040–2069) and 2080s (2070–2099). Drought threshold uncertainty shown in orange, model parameter uncertainty in blue, future scenario uncertainty in green and drought index uncertainty in tan.

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