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The impact of climate mitigation on projections of future drought

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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. Our study considers both climate model uncertainty associated with future climate projections, and future emissions of greenhouse gases (future scenario uncertainty). Four drought indices (the Standardised Precipitation Index (SPI), Soil Moisture Anomaly (SMA), the Palmer Drought Severity Index (PDSI) and the Standardised Runoff Index (SRI)) 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 (“the 2080s”). We consider where there are statistically significant increases or decreases in the proportion of time spent in drought in the 2080s compared to the baseline. 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 drought is generally projected for the Amazon, Central America and South Africa whilst projections for northern India consistently show significant decreases in time spent in drought. Whilst the patterns of changes in future drought were similar between scenarios, climate mitigation, represented by the RCP2.6 scenario, tended to reduce future changes in drought. In general, climate mitigation reduced the area over which there was a significant increase in drought but had little impact on the area over which there was a significant decrease in time spent in drought.

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 (Confalonieri et al., 2007). 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 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, and 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, four of which have been used in this study, as outlined in Sect. 3.1, although our study only considers physical droughts (using meteorological, agricultural and hydrological drought indices), each of which incorporate different features of physical droughts (Wilhite and Glantz, 1985).

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 (Douveille et al., 2002; Wetherald and Manabe, 2002; Burke et al., 2006; 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 longer droughts have also been observed in some semi-arid and sub-humid regions, including Southern Europe and West Africa (IPCC, 2012), while droughts have become less frequent, less intense, or shorter in some regions such as central North America and northwestern Australia. However, these findings were largely based on studies using the Palmer Drought Severity Index (PDSI) and the reported increases in global drought may have been overestimated because of the simplified calculation of potential evaporation used in the PDSI. Calculations based on the underlying physical principles, considering changes in available energy, humidity and wind speed, suggest little change in drought over the past 60 yr (Sheffield et al., 2012).

The regions which have already experienced increasing drought hazards may therefore be particularly sensitive to any projected increases in physical drought hazards. It is considered likely that the extent of drought-affected areas will increase in the future with climate change (Kundzewicz et al., 2007). Temperature, precipitation and evapotranspiration are major drivers of drought. Temperature and evapotranspiration are projected to increase over most land areas, while increases in global mean precipitation are projected, but with strong regional differences, including a projected decrease in precipitation in sub-tropical regions and increases at 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. The regions where there is most confidence in future physical drought increases include southern Europe and

the Mediterranean, central Europe, central North America, Central America and Mexico, northeast Brazil, and southern Africa (IPCC, 2012).

However, drought is not solely affected by climatic drivers, and 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 taken into account to gain a complete understanding of future drought events and their impacts, although these factors are not included in the present study, which focuses only on physical drought hazards (using agricultural, meteorological and hydrological indices).

Improving an understanding of uncertainties 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). Model projections of future climate change contain uncertainty due to three key sources: internal (or natural) variability, modelling uncertainty, and emissions uncertainty (Hawkins and Sutton, 2009). The dominant source of uncertainty varies with variable, region and time horizon (Hawkins and Sutton, 2009). In the case of global temperature changes, internal variability is the dominant source of uncertainty on short-term (decadal) timescales; emissions become increasingly important for lead times beyond around 40 yr, and modelling uncertainty has a larger influence on longer-term projections (end of the century). The total uncertainty increases with time (Hawkins and Sutton, 2009). However, the dominant source of uncertainty also depends strongly on region and on the variable considered (Hawkins and Sutton, 2011). The aim of the present study is to assess the impact of climate mitigation policies on future drought projections. 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. This study differs from the earlier, related studies of Burke et al. (2006) and Burke and Brown (2008) in that it uses a different ensemble of climate models driven by two future climate scenarios, and applies a range of plus the SRI index was added in the present 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 metrics available, reflecting the different aspects of the hydrological cycle. Four are considered here, covering different kinds of drought: the Standardised Precipitation Index (SPI) gives an indication of meteorological drought; the Soil Moisture Anomaly (SMA) sits somewhere between meteorological and hydrological

Table 1. The end-of-century range of atmospheric CO₂ concentration (extract from Booth et al., 2012, 2013), temperature and precipitation given by the ESE simulations for the SRES A1B and RCP2.6. CO₂ is the 2099 value. Temperature and precipitation are based on the end-of-century 10 yr average (2070–2099) relative to the 1961–1990 average, over all global land points. Values in parentheses exclude cold regions as described in the text.

	A1B			RCP2.6		
	10th	median	90th	10th	median	90th
Atmospheric CO ₂ concentration (ppmv)	635	794	972	390	449	514
Land temperature change (°C)	4.0 (3.9)	5.2 (5.1)	6.9 (6.8)	2.1 (2.1)	3.0 (2.9)	3.8 (3.7)
Land precipitation change (%)	2.5 (−0.0)	5.4 (3.3)	7.4 (5.7)	3.0 (1.6)	4.2 (3.1)	6.4 (5.1)

drought and can be used as an indicator of agricultural drought; the widely used Palmer Drought Severity Index (PDSI), is also considered to be mostly an indicator of meteorological drought; and the Standardised Runoff Index (SRI) represents hydrological 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.

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. The use of an ensemble of climate model projections, and two future scenarios enables the assessment of uncertainties in future drought projections from these two sources. It should be noted that a small uncertainty range does not necessarily imply greater confidence in the projections, for example if the model/index provides inaccurate projections.

2 Climate model simulations

In this study we use a large ensemble of climate change simulations with different configurations of HadCM3C (Booth et al., 2012, 2013), a coupled atmosphere-ocean-carbon cycle Earth system model. The model is configured from HadCM3 (Gordon et al., 2000), a widely studied coupled ocean-atmosphere model used by the Met Office 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).

In HadCM3C, runoff and soil moisture are calculated by the Met Office Surface Exchange Scheme Version 2 (MOSES2 – Essery et al., 2001, 2003; Cox et al., 1999).

There are there are four soil layers in MOSES2, each with a temperature, and moisture content with thicknesses from the surface downwards, of 0.1, 0.25, 0.65 and 2.0 m. The soil hydrology component of MOSES is based on a finite difference form of the Richards equation (Richards, 1931). The water flux which enters the soil at the surface is the sum of the throughfall and snowmelt minus surface runoff. The lower boundary condition assumes free drainage (Cox et al., 1999). Transpiration through plants extracts soil moisture directly from each soil layer via roots and bare soil evaporation depletes moisture from the top soil layer. The ability of roots to access moisture in each soil layer is determined by a root density distribution; root density is assumed to follow an exponential distribution with depth.

The design and setup of the 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., 2012, 2013), 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. Note that these two scenarios are from different “families”, but were the datasets available from the ESE. 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 CO₂

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 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

Results were analysed for 2070–2099 (“the 2080s”) and compared with the baseline period (1961–1990).

3.1 Application of drought indices

Four indices of drought are calculated and analysed, the SPI, the SRI, the SMA and the PDSI, using an approach similar to that of Burke and Brown (2008). Details of each of these indices and their application in the present study are provided below. As noted in the introduction, the indices chosen represent different kinds of drought, and exhibit different uncertainties because they are related with processes that are either difficult to observe over large areas (e.g. soil moisture, runoff) or difficult to parameterize due to lack of process knowledge.

3.1.1 Standardised Precipitation Index (SPI) and Standardized Runoff Index (SRI)

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; Hayes et al., 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 variation of the impacts of reduced precipitation with event duration (Sivakumar et al., 2010).

The present study predominantly uses a twelve-month accumulation period, although Vidal et al. (2012) note that the response of drought to climate change can be highly sensitive to the timescale considered. We therefore also include SPI calculated on a range of different timescales (1, 3, 12, 18 and 24 months). 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 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 following the approach of Burke and Brown (2008), from climate model monthly precipitation that was normalised around the baseline thirty-year distributions for each model grid square. Following Burke and Brown (2008), the SPI is estimated by transforming the long-term precipitation distribution for each location to a normal distribution (Guttman, 1999). The location-specific parameters used to transform the baseline precipitation distribution were also used to transform the future precipitation distribution.

The SRI was calculated in an analogous fashion to the SPI but using the modelled monthly mean runoff time series for each grid cell. This is a recently adopted index (Shukla and Wood, 2008) which can be used to evaluate hydrological droughts or as a proxy for river discharge (e.g. Joetzjer et al., 2012).

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 collected over large areas, 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 CO₂ physiological effects if these are included in the climate model and the effect of any included feedbacks on climate projections (as in the present study).

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 1m 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. The SMA was calculated at timescales of 12 months, for the top 1m of the soil by subtracting the soil moisture climatology (Burke and Brown, 2008), and the resulting data were not normalised by the standard deviation.

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

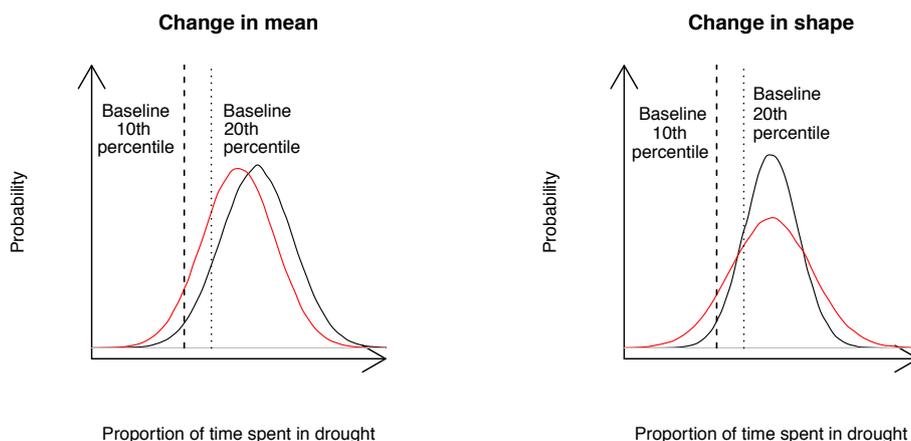


Fig. 1. Schematic of drought threshold. The black line represents a sample baseline distribution and the red line a sample future distribution.

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., 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 sufficiently (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 lack of soil moisture heterogeneity 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. Potential evaporation is calculated with the Penman–Monteith equation (from temperature, relative humidity, pressure, wind and short- and longwave radiation), following the methodology of Burke et al. (2006). The calculation of potential evaporation is strongly sensitive to formulation choices (e.g. timestep) and to the quality of input variables (Kay and Davies, 2008). The PDSI has a memory of the order of 12 months, resulting in the use of this timescale for the other indices (Burke and Brown, 2008). Calibration parameters determined for each location under baseline climate conditions were held constant when calculating the PDSI for future conditions.

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 four 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, 2013) 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, normalised 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. 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. 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. Therefore this exemplar approach will maintain consistency with these and enable comparison with other related studies using the ESE (e.g. Lambert et al., 2012; Hartley et al., 2013; Murphy et al., 2013). However, we note the following limitations: (a) our study has a global focus, and the exemplar selected on countries may bias toward larger countries and regional biases; and (b) selection of the average response over countries may limit applicability at the

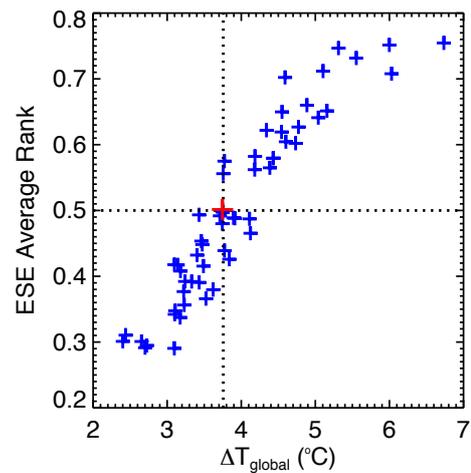


Fig. 2. The ESE members ranked by their A1B end-of-century temperature response and percentage precipitation change, averaged over the four seasons for 24 selected countries as a function of their 2080–2099 annual global temperature response with respect to 1961–1990. The exemplar member selected to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

regional scale where drought assessments are useful (and potentially used). Discussion of the regional behaviour of the ESE is included in Murphy et al. (2013).

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. While time in drought is the most basic drought characteristic, the final impact often depends on spatio-temporal characteristics (Vidal et al., 2010).

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 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). This is because the PDSI does not include frozen processes, so would likely have large errors in these regions. 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, 2013; 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. The consensus maps (Fig. 5) are only presented for 10th percentile calculations.

4 Results

Here we present our results for the proportion of time spent in drought for the four 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.

4.1 Climatic variables

Both temperature and precipitation influence the processes leading to drought events so understanding how those variables are projected to change can help understand 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 temperature changes across the model ensemble is much larger for the A1B scenario

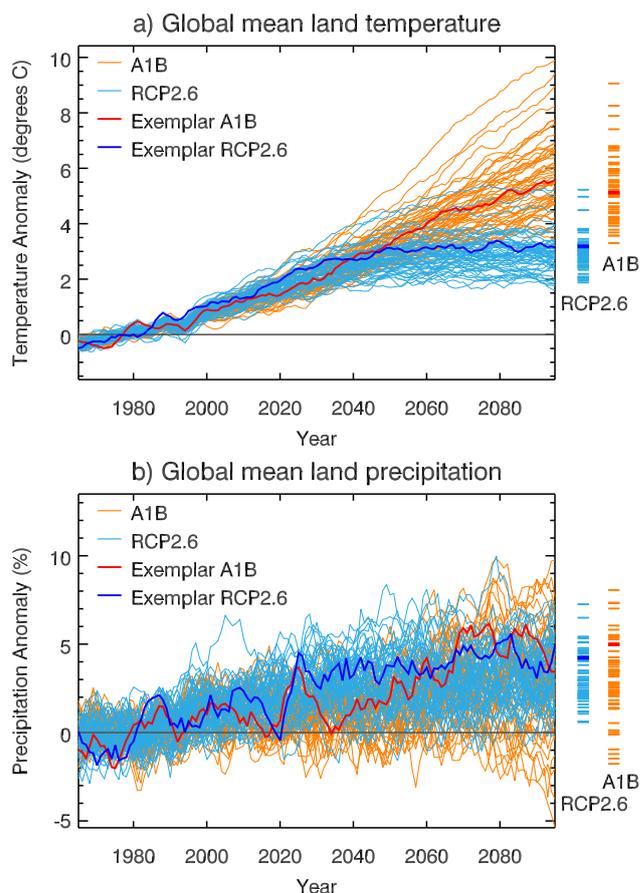


Fig. 3. Annual mean temperature (a) and percentage precipitation (b) anomalies (with 5 yr smoothing) from 1961 to 2099 (relative to the 1961 to 1990 average) averaged over land points, excluding cold regions, for the ESE simulations. The A1B future scenario is shown in orange and RCP2.6 is shown in blue (individual 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.

than for the RCP2.6 scenario; a wider range of responses is expected given the larger forcing in the A1B simulations. 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

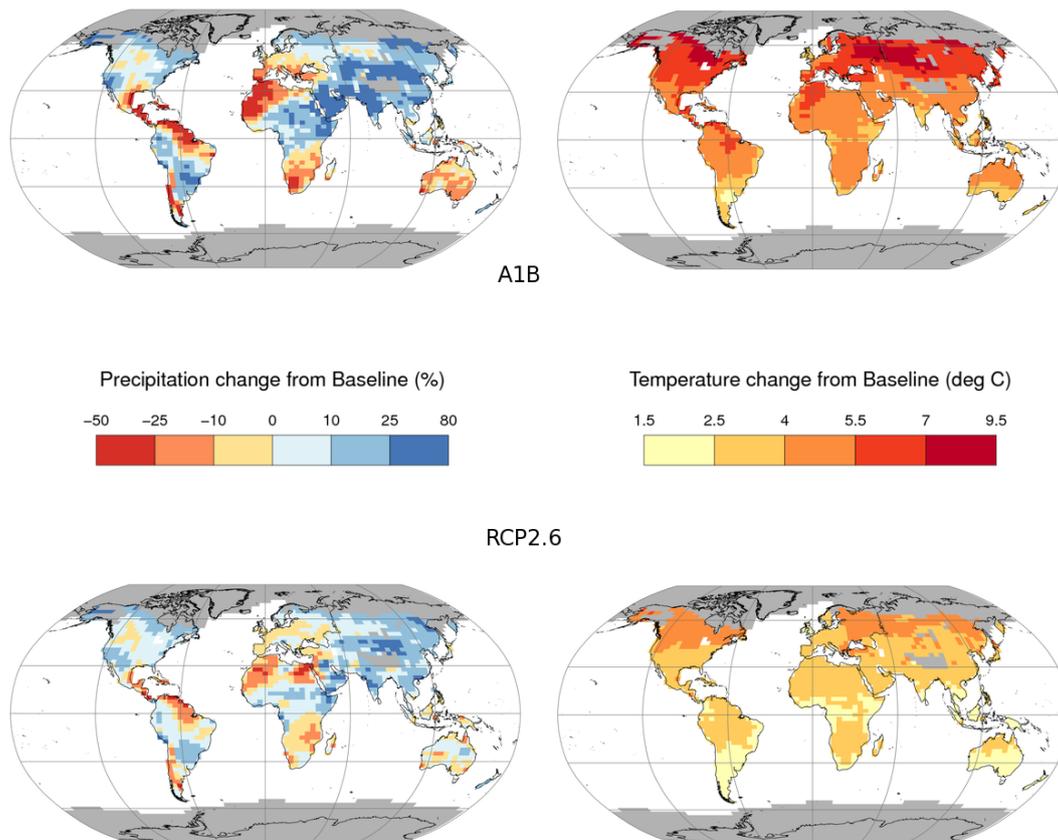


Fig. 4. Precipitation (left panels) and temperature (right panels) anomalies for the 2080s (1970–2099) from the baseline 1961–1990 for the exemplar model of the ESE for A1B (top panels) and RCP2.6 (bottom panels) future scenarios. Grey regions represent the excluded cold regions.

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 four drought indices, for the 10th percentile calculations only. 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 SRI drought show the least model agreement across the ESE model ensemble for either significant increases or decreases. For some regions there is a consistent signal across the SPI, PDSI and SMA 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, northwestern Africa and parts of South Africa for these three drought indices. There is also some indication of a significant increase in the SRI drought for these regions. In general, projections of PDSI drought have the strongest model agreement and largest spatial extent across those regions. Significant decreases were projected for northern India, parts of central Asia and parts of East Africa for all four 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

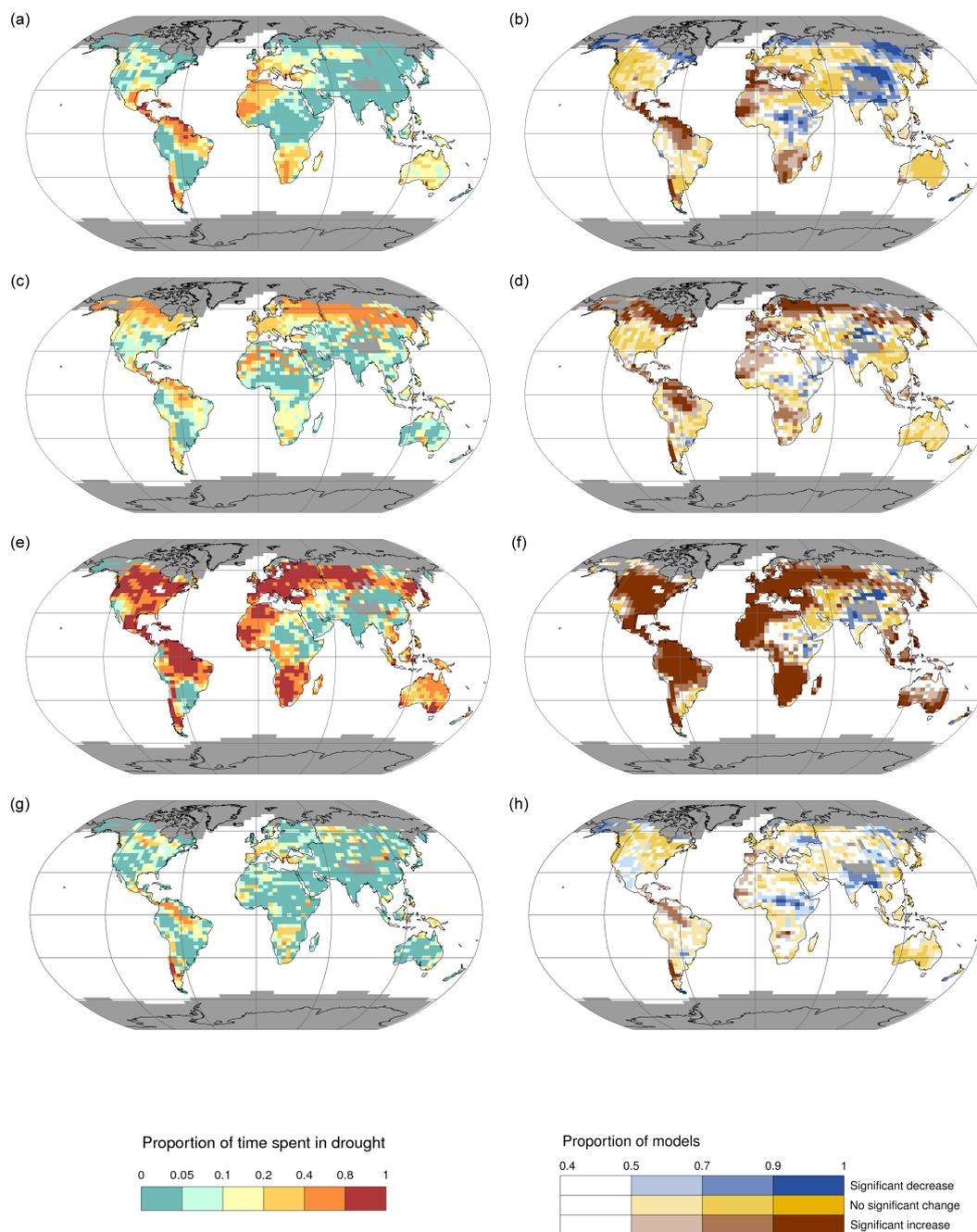


Fig. 5. The proportion of time spent in drought for three drought indices from the ESE for the A1B future scenario in the 2080s (2070–2099), exemplar model (left) and model agreement of significant changes (right). (a) and (b) are the SPI, (c) and (d) are for the SMA; (e) and (f) are for the PDSI; and (g) and (h) are for the SRI. Grey areas represent the excluded cold regions. Results shown are for the 10th percentile calculations only.

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 difference between the SPI and PDSI/SMA projections in high latitudes is likely to be due to high-latitude temperature amplification, since SPI does not

include temperature, while SMA and PDSI do. In addition, the SPI and PDSI will not include the impact of changes in snow and soil freezing, which may impact drought projections at high latitudes. The patterns of projected temperature changes (Fig. 4) suggest that temperature changes in these regions may have a greater influence on drought

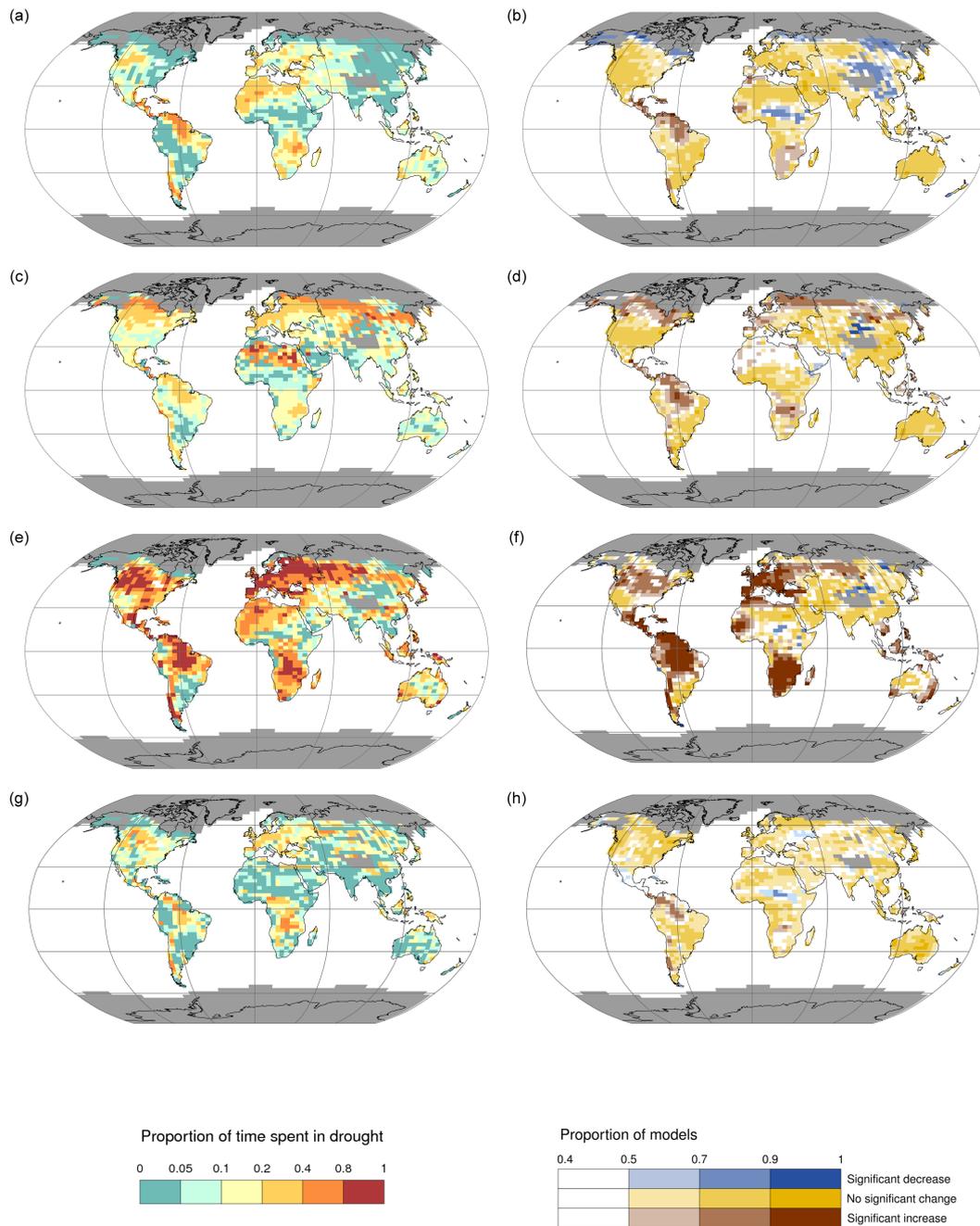


Fig. 6. The proportion of time spent in drought for three drought indices from the ESE for the RCP2.6 future scenario in the 2080s (2070–2099), exemplar model (left panels) and model agreement of significant changes (right panels). (a) and (b) are the SPI, (c) and (d) are for the SMA; (e) and (f) are for the PDSI; and (g) and (h) are for the SRI. Grey areas represent the excluded cold regions. Results shown are for the 10th percentile calculations only.

projections using the SMA and PDSI than precipitation changes. The SRI shows little agreement between models at these latitudes.

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 SRI projections than for the other three drought indices. This may have been because the time spent in drought in the 2080s was generally smaller for the SRI than the other indices. In addition, while the SMA used only the top three soil layers to calculate drought, the SRI is

based on both surface and subsurface runoff from the whole soil profile. Subsurface runoff changes are likely to be more damped (and less strongly related to changes in upper layer soil moisture) than surface runoff changes. This may partly explain the weaker signals seen in the SRI compared to the SMA. In some cases, regions with no significant change correspond to regions with lower model agreement for precipitation changes, as was the case for the other indices. However, the precipitation projections shown are for all changes rather than just those that are significantly different from the baseline.

Figure 5 (left panels) shows the proportion of time spent in drought in the 2080s for each model grid square for the A1B exemplar model (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 a decrease. For the exemplar model, the PDSI suggests high proportions of time spent in drought (> 80 %) for some regions, which is greater than the values found by Burke et al. (2006) and Burke and Brown (2008). This may be due to the greater warming in the ESE compared to the climate models studied by Burke et al. (2006) and Burke and Brown (2008). 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 panels) 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 Uncertainties in future drought projections

Uncertainties in future drought projections were represented 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 four 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). SRI drought shows the lowest percentage of the land surface with a significant increase in time spent in drought (with values ranging between 15–50 % for the A1B scenario and similar for the RCP2.6 scenario) and the highest with a significant

decrease. As Fig. 5 shows, both SPI and SRI projections tend to show more significant decreases in time spent in drought whilst the SMA and PDSI projections tend to show more significant increases. This would explain, for example, the lower percentage of the land surface with a significant increase for SRI and the higher significant decreases found with the SRI (as in Fig. 7). Projections for SMA drought fall between the small increase in SRI and SPI drought and the large increase in the PDSI drought, 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 increase in SRI drought, most likely because it is only a small change 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, SRI 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 fewer 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 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.

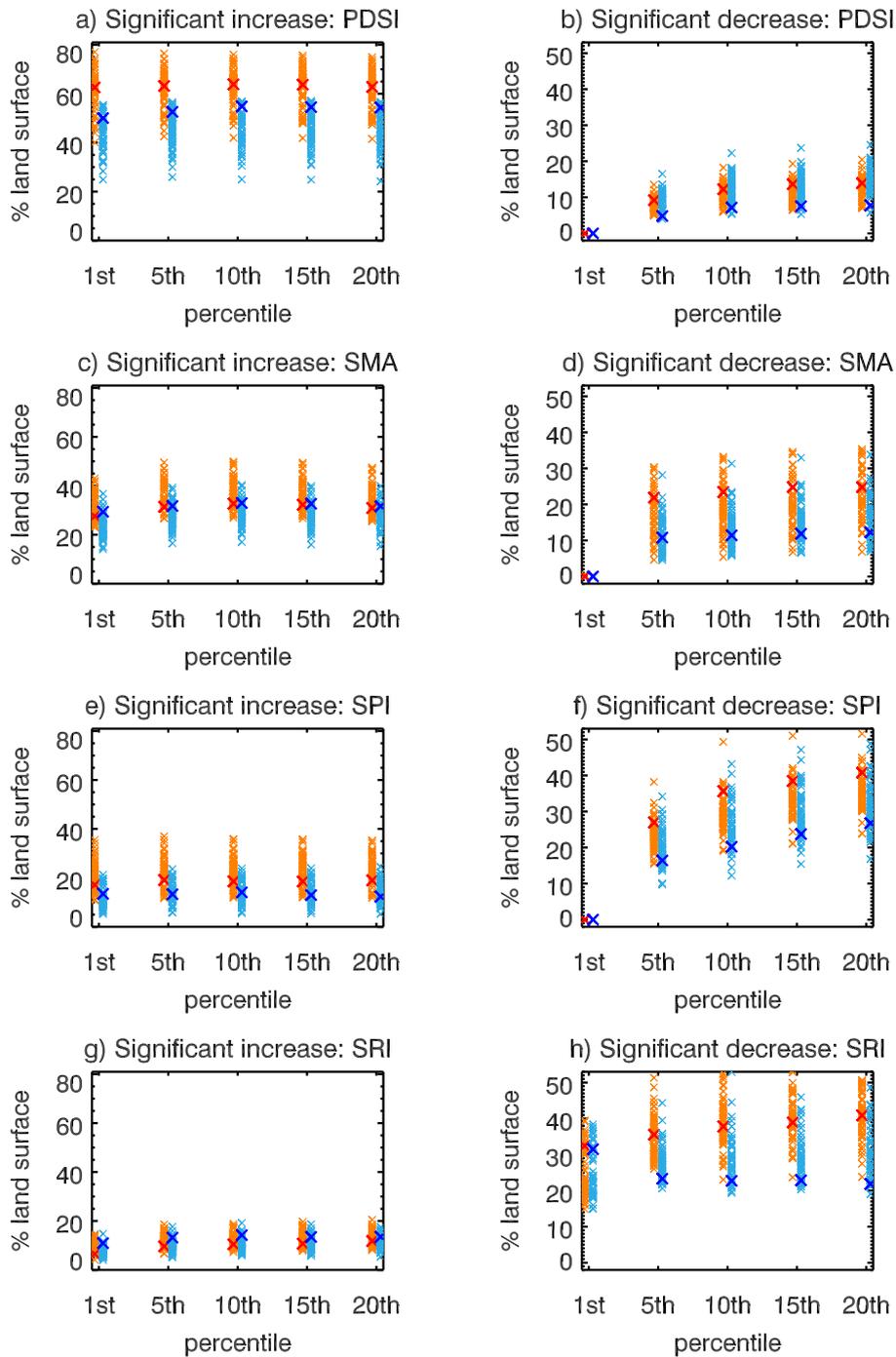


Fig. 7. The percent of the land surface (non-cold areas) with significant changes (as defined in Sect. 3.1) in the time spent in drought in the 2080s (2070–2099) as given by the ESE (increases – left column, and decreases – right column) for the four drought indices SPI: (a), (b); SMA: (c), (d); PDSI: (e), (f) and SRI: (g) and (h) as a function of drought threshold. 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).

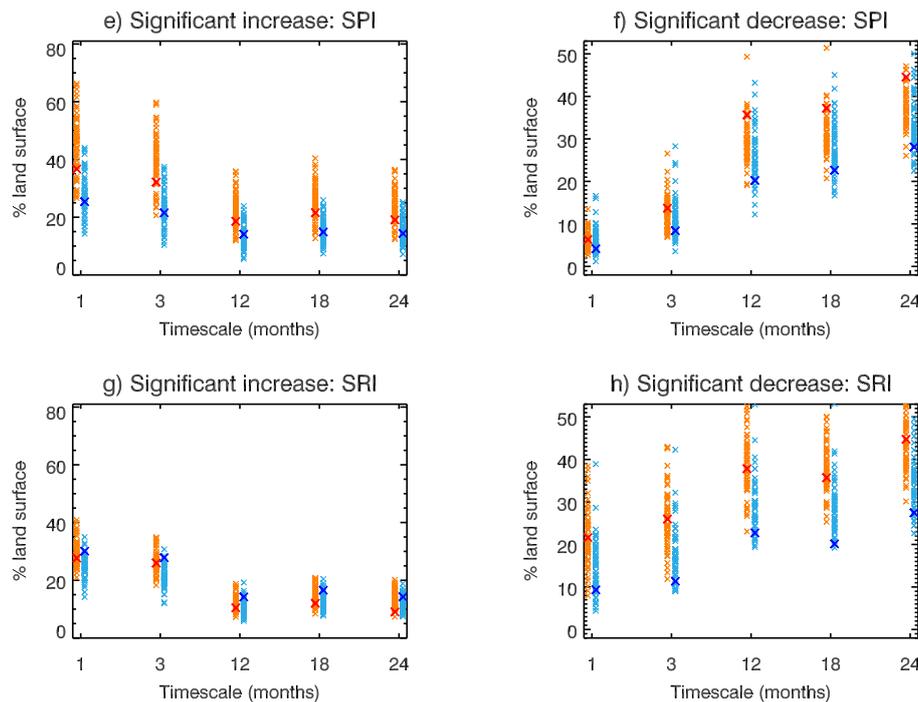


Fig. 8. The percent of the land surface (non-cold areas) with significant changes (as defined in Sect. 3.1) in the time spent in drought in the 2080s (2070–2099) as given by the ESE (increases – left column, and decreases – right column) for the SPI: (a), (b); and SRI: (c) and (d) at the different integration timescales. 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).

Figure 8 shows the dependence of the SPI and SRI drought on the timescales. Any changes at the 12-, 18- and 24-month timescales are very similar for both drought indices, suggesting that the SPI and SRI shown in Fig. 7 are more representative of annual timescales and above. At the 1- and 3-month timescales, the ensembles generally show more areas with a significant increase in drought and a smaller area with a significant decrease in drought. Model spread within the ensembles is also larger at these timescales.

5 Discussion

5.1 Drought indices

We find considerable differences in future projections of time spent in drought between the four drought indices used in this study, the SPI, SRI, 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 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; similar findings were made by Joetzjer et al. (2012) who compared three drought metrics over two river basins. 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 the drought metrics, time series of runoff, precipitation, soil moisture, and the PDSI, are, as expected, primarily driven by differences in the climatic variables upon which they are based, particularly precipitation and temperature (Burke, 2011). Burke (2011) showed that metrics based on precipitation, soil moisture and the PDSI 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. This is expected since the SPI and precipitation percentile thresholds are equivalent.

Regions with a strong decrease in precipitation are projected to experience increases in time spent in drought for all four drought indices, whereas regions with strong projected increases in temperature tend to give divergent results across

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
SRI (Standardised Runoff Index) (Shukla and Wood, 2008)	Hydrological	Runoff	Based on method for SPI but with runoff; includes broader effects than just precipitation; as for SMA, can be calculated within a climate model thus including feedbacks.	No direct observations of un-routed runoff; however flow gauge measurements of stream flow may serve as a proxy.

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 PDSI is known to be particularly sensitive to temperature, largely due to its representation of (and the influence of temperature on) evapotranspiration (Sheffield and Wood, 2011; van der Schrier et al., 2011). The reduced uncertainty associated

with temperature projections results in reduced uncertainty in PDSI drought projections.

Soil moisture and runoff are strongly linked to vegetation and land use change. In vegetated regions, increased atmospheric CO₂ concentrations may fertilise plant growth and influence changes in soil moisture. Increasing CO₂ 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; Gedney et al., 2006; Wiltshire et al., 2013). However, a recent study has shown much more uncertainty in runoff responses to elevated CO₂ than previously

considered (Davie et al., 2013), finding that both positive and negative overall effects could result depending on the model used and the relative strength of competing effects. We have not attempted to separate vegetation changes or CO₂ 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/SRI, 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 future physical drought changes. It is therefore recommended to adequately choose an appropriate drought index to represent the vulnerability of the chosen hydrosystem.

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., 2012, 2103). 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 SMA and the SRI are the only drought indices that will be directly influenced by perturbations in CO₂ concentrations and resultant impacts on vegetation fertilisation and runoff, since they are calculated directly from model output that included the MOSES2 land surface scheme (Essery et al., 2003). 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 CO₂ physiological effects. Instead, a spectrum of CO₂ physiological effects is applied (Booth et al., 2012, 2013), resulting in each ensemble member having a slightly different impact. This could explain differences between the SMA/SRI and the SPI, and would influence the ensemble range for SMA only. Further work could investigate the relative influence of atmosphere and C cycle meta-parameters used in the ESE, for instance by performing an ANOVA analysis (e.g. Vidal and Wade, 2008).

5.3 Future scenarios uncertainty – the impact of climate mitigation

We have used two future scenarios in this study defined using different 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 a 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 differences in the scenarios, the difference between them can be used to indicate the potential impact of climate mitigation on future drought projections. However, 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. Even under the RCP2.6 mitigation scenario, there were still large increases in drought in many regions. 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 for significant increases than decreases in time spent in drought for all four 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 four 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 strongly influenced by temperature, via its impact on evapotranspiration (Sheffield and Wood, 2011; Van der Schrier et al., 2011).

Some regions show opposing precipitation signals between the future scenarios in the exemplar simulation; for example, Texas and southeastern Europe show a drying

under A1B and a wetting under RCP2.6, reflected in projections of SPI drought for those areas, which may be related to decadal variability. Knowledge of the climatic processes leading to these projected changes may aid understanding of how mitigation actions may influence drought occurrence regionally. For example, Murphy et al. (2013) note that internal variability plays a strong role in driving the spread of precipitation responses in the ESE projections used here. Murphy et al. (2013) discuss the mechanisms behind precipitation changes in the ESE, including the importance of the use of flux adjustments in the ESE to ameliorate historical sea surface temperature (SST) biases, which can potentially alter the relationship between future changes in tropical SSTs and precipitation, the effects of Amazon forest die-back on regional precipitation (Betts et al., 2004; Falloon et al., 2012), and the strong response of HadCM3 family models to El Niño-like patterns of future SST change in the tropical Pacific Ocean (Cox et al., 2004).

5.4 Drought thresholds

Our results show very little effect of drought thresholds on the proportion of time spent in drought. The percent of the land surface with a significant increase in time spent in drought is minimally influenced by choice of drought threshold, indicating changes in the distribution mean (Fig. 1). However, higher thresholds generally produced a larger percent of the land surface with a significant decrease in time spent in drought, particularly for the SPI. Significant decreases in PDSI drought give a slightly larger ensemble spread for higher thresholds, potentially suggesting a change in the shape of the distribution (Fig. 1). This suggests that choice of drought threshold is of less importance when conducting impacts assessments of changes in future physical drought hazards. The choice of drought index should be conditioned by the specific hydrosystem studied. However, there are inevitably “threshold effects” when considering socio-economic droughts that are related to thresholds in physical droughts.

5.5 Uncertainty in context

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 four drought indices. This may have implications for drought management planning in the future, although the present study has only considered physical drought hazards, while socio-economic drought risks result from a combination of both (physical) hazard and vulnerability. Whether physical drought hazards relate to socio-economic impacts depends on which areas are affected. For instance, non-vulnerable areas may experience large increases in drought without noticeable socio-economic impacts; conversely an increase in drought in areas with important crop production could have large impacts. An improved understanding of socio-economic drought impacts required the inclusion of anthropogenic hydrosystems within Earth System models.

Samaniego et al. (2013) showed that the parametric uncertainty of a given land surface model used to estimate a soil moisture index over Germany was the key factor for drought identification. Ignoring parametric uncertainty could lead to a large amount of false positives (i.e. identifying a drought when in fact there is no drought). This is an important issue in drought analyses driven by GCMs, particularly for indices using variables derived from the GCM land surface scheme (LSS) such as soil moisture (SMA) and runoff (SRI). However, the SMA and SRI generally produced weaker estimates of future changes in drought, compared to the other indices studied here. The ensemble studied here only sampled some of the parametric uncertainty space associated with the LSS, specifically those related to the land carbon cycle, not all of which will have a significant impact on soil moisture or runoff. Therefore a fuller insight into uncertainties in future drought projections may require a more comprehensive GCM ensemble designed to capture a wider range of LSS parametric uncertainties. Alternatively, this may be achieved by combining a GCM ensemble such as that studied here with an ensemble of stand-alone LSS simulations in which a fuller range of key parameters are varied.

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. For reference, ESE A1B simulations

show ranges of future global and regional surface temperature changes which are broader, and shifted to warmer values, compared to CMIP3 multi-model results (Murphy et al., 2013), as used in the previous IPCC report (IPCC, 2007). This is related to the global impacts carbon cycle and physical climate feedbacks in the ESE, and regional impacts of interactions between terrestrial ecosystem and physical climate processes, which were not represented in the CMIP3 experiments. While the present study applied raw climate model outputs, further uncertainties may be introduced via bias-correction in climate impact studies (e.g. Ehret et al., 2012). 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.

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.

In the present study, the spatial patterns of changes in future droughts were generally similar between future scenarios. Climate mitigation (under the RCP2.6 scenario) generally reduced future changes in drought, compared to the business-as-usual scenario (A1B) and had a larger impact on significant increases than decreases in time spent in drought.

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. Despite large overall uncertainties in future drought projections, consistent signals are apparent for some regions. For most of the indices studied here, an increase in time spent in drought in the 2080s was projected across the Amazon, Central America and South Africa whilst a decrease was shown over northern India, with smaller changes suggested by the SRI. In general, more of the land surface is projected to have an increase in time spent in drought than a decrease. The drought indices studied here represent different types of drought, and exhibit different uncertainties because they are related with processes that are either difficult to observe over large areas (e.g. soil moisture, runoff) or difficult to parameterize due to lack of process knowledge.

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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