Refining projections of future temperature change in West Africa

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ABSTRACT: Future warming in West Africa will have a detrimental effect on the communities living there. To support assessments of climate change impacts, we propose a method for refining regional temperature projections and demonstrate its application to West Africa for the mid-21st century. Our focus is on characterising uncertainty more comprehensively by considering projections of global warming. We calculate a transformation between a frequency distribution of global warming values derived from the Coupled Model Intercomparison Project phase 5 (CMIP5) models and a broader published probability distribution of global warming developed by the Met Office. The latter draws on perturbed parameter ensembles of simpler climate models to account for uncertainties related to the atmosphere, ocean, carbon cycle and aerosol processes that are not well characterised by the CMIP5 ensemble. Noting that West African warming is highly correlated with global warming in the CMIP5 ensemble, and that a significant portion of the uncertainty in projected West African warming arises from the uncertainty in global warming, we then apply the same transformation to CMIP5-derived distributions for warming in different regions of West Africa. The resultant regional warming distributions have longer tails than distributions estimated directly from the CMIP5 ensemble. Our results imply that CMIP5-based assessments of temperature-sensitive applications may underestimate the probability of large (and small) impacts. Our method could be used to refine temperature projections for other regions of the world in which regional temperature changes are highly correlated with global mean temperature changes.

KEY WORDS: Climate change · Impact assessment · Climate model · Multi-model ensemble · Risk management · Uncertainty · Quantile mapping · Sahel

1. INTRODUCTION

Projections of future regional climate changes are an important source of information for stakeholders making long-term decisions about climate-sensitive activities. However, these projections include significant uncertainties that make using them in this way challenging. For example, there are uncertainties in the future forcing of the global climate system by anthropogenic emissions, how the climate system will respond to this forcing on global and regional scales,

and unforced climate variability. The contribution to the total uncertainty from these different components varies depending on the climate variable, time horizon, location and size of region under consideration (Hawkins & Sutton 2009, Rowell 2012). The sources of uncertainty often include the Global Climate Models (GCMs) that regional climate change projections typically rely on. GCMs represent only part of our incomplete understanding of the global climate system. For example, our current understanding of many processes (e.g. atmospheric convection)

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cannot be represented explicitly in long climate simulations due to limitations in available computer power, and must be parameterised. Different GCMs use different parameterisation schemes, contributing to significant uncertainties in GCM projections. However, it has also been recognised that climate projections derived directly from commonly used ensembles of GCMs do not account for the full range of uncertainty in future climate changes. For example, in the future projection simulations contributed to the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al. 2012), each GCM uses a single set of values for uncertain internal model parameters and, in most cases, does not represent uncertainties in the response of atmospheric carbon dioxide concentrations to carbon dioxide emissions. The resulting ‘overconfidence’ in climate projections could lead to an underestimation of risks due to climate change (e.g. Brown & Wilby 2012) and result in maladaptation.

This paper describes research done as part of the AMMA-2050 project, which supported climate-resilient development in West Africa. The methods described are applicable to other regions, but the paper focusses on uncertainties in future temperature changes for West Africa. Rowell et al. (2016) demonstrated the significant scale of these uncertainties. Examining just the uncertainty expressed by CMIP5 simulations of a single scenario for atmospheric greenhouse gas concentrations, consistent with Representative Concentration Pathway 8.5 (RCP8.5), they showed that temperature increases in the Sahel between 1951–2000 and 2041–2060 ranged from $< 0.5^{\circ}\text{C}$ to $> 4^{\circ}\text{C}$, with $> 85\%$ of this range being due to different responses of the GCMs to forcing, rather than to unforced climate variability. The size of this temperature range and the possibility that it is overconfident have important implications, as future temperature changes could have substantive impacts on the systems supporting the well-being of people in the region. For example, cereal crops are important sources of food in West Africa and the crop modelling study of Sultan et al. (2013) showed a decline in potential crop yields with increasing temperature.

In this paper, our aim is not necessarily to reduce the uncertainty in projections of future temperature change in West Africa. Instead, we aim to contribute to the provision of more useful information for impacts science and regional stakeholders by demonstrating a method to better characterise the uncertainty in regional temperature projections. We focus on refining projections of future temperature change in West Africa by better accounting for un-

certainities in global average warming. The rationale for this is that we understand anthropogenic warming of the climate as a globally coherent phenomenon. Previous studies (e.g. Sutton et al. 2015) have investigated the link between change in global average temperature and regional temperature changes around the world, and we specifically investigate this for West Africa. We also note the relationship between local temperature changes and changes in global average temperature in the pattern scaling technique often used in the production of climate change projections (e.g. Mitchell 2003, Suppiah et al. 2007, Tebaldi & Arblaster 2014).

Section 2 of this paper investigates links between future changes in temperatures in West Africa and changes in global average temperature simulated by the CMIP5 GCMs. Having established the strength (and limits) of the relationships between regional and global mean temperature changes in the CMIP5 ensemble, in Section 3, we develop a transformation that can be used to incorporate information on future change in global mean temperature from beyond CMIP5 into regional temperature projections and apply it to West Africa. Section 4 comments on the resulting refined temperature projections, discusses the merits and broader applicability of our approach and notes avenues for further work.

2. UNDERSTANDING INTER-MODEL DIFFERENCES IN FUTURE TEMPERATURE CHANGE IN WEST AFRICA

This section examines correlations across the CMIP5 GCM ensemble between changes in seasonal mean temperatures in West Africa over the 21st century and corresponding changes in annual mean global average temperatures. This cross-GCM analysis of local seasonal mean temperatures is intended to be more pertinent to uncertainties in multi-model projections of seasonal mean temperatures for West Africa than previous studies. For example, it contrasts with the global study of Sutton et al. (2015), who analysed time series of local and global average temperature over the 21st century from 3 selected CMIP5 GCMs, and did not provide results for different seasons of the year.

The most pronounced feature of the West African climate is the West African Monsoon. This has the potential to complicate links between temperature changes in West Africa and changes in global average temperature. This section recognises this and

also uncovers relationships between changes in regional temperature and changes in precipitation in the region.

2.1. Materials and Methods

2.1.1. Data

We analyse anomalies in climatological annual and seasonal mean data from 39 different CMIP5 GCMs (see Table S1 in the Supplement at www.int-res.com/articles/suppl/c082p001_supp.pdf). To maximise the forced signal in relation to the ‘noise’ of unforced climate variability, we analyse climate changes to the end of the 21st century, between 1986–2005 and 2081–2100, under RCP8.5 (see Moss et al. 2010), the highest forcing scenario considered by the Intergovernmental Panel on Climate Change’s Fifth Assessment Report (IPCC 2013a). Prior to analysis, data from all 39 GCMs are regridded to the 1.875° longitude by 1.25° latitude grid of the atmosphere component of the HadGEM2-ES GCM.

2.1.2. Analysis of gridded data

Processes contributing to the differences in temperature anomalies simulated by the 39 different GCMs are explored by seeking robust relationships between changes in seasonal mean temperatures at each grid cell (hereafter ‘local’ temperature changes) and changes in global average annual mean temperature and local seasonal mean precipitation. This is done for each grid cell by regressing the temperature changes for that cell (i.e. 39 local values, 1 for each of the 39 GCMs) against the 39 values of changes in the other variables (i.e. global average temperature and/or local precipitation). To be clear, this regression is performed in GCM space, not, for example, in temporal space (i.e. between 2 time series), as is often done in climate science. Note also the use of global annual mean temperature rather than global seasonal mean temperature. Although we might expect slightly more robust global–local relationships for contemporaneous seasons, relationships with annual global mean temperature are more useful, due to the extensive research dedicated to assessing and understanding its sensitivity to anthropogenic emissions.

Three statistical models for the inter-GCM variance of local seasonal mean temperature change were trialled:

$$\Delta T_{\text{loc}}^m = \alpha \Delta T_{\text{glo}}^m + \epsilon^m \quad (1)$$

$$\Delta T_{\text{loc}}^m = \alpha \Delta P_{\text{loc}}^m + \epsilon^m \quad (2)$$

$$\Delta T_{\text{loc}}^m = \alpha \Delta T_{\text{glo}}^m + \beta \Delta P_{\text{loc}}^m + \epsilon^m \quad (3)$$

where ΔT_{loc}^m , ΔT_{glo}^m and ΔP_{loc}^m are changes in local seasonal mean temperature, global average annual mean temperature and local seasonal mean precipitation respectively simulated by GCMs $m = 1, 2, 3, \dots, 39$, α and β are regression coefficients and ϵ^m are residuals representing variance not explained by the statistical model.

The statistical models are initially assessed by calculating values of Pearson’s R correlation coefficient (computed in GCM space, consistent with the definition of the statistical models). We then compute the inter-GCM variance in local temperature change that is explained by each statistical model and compare this between the 3 models. The explained variance is measured by the adjusted R-squared statistic (Miles 2014), which accounts for the tendency of Eq. (3), with 2 predictor variables, to explain more variance by chance than Eqs. (1) or (2), which each have a single predictor. It is a function of Pearson’s R correlation that becomes smaller with the number of predictor variables for a constant value of Pearson’s R.

2.1.3. Analysis of regional averages

To inform regional climate projections, the analysis of local temperature changes (i.e. temperature changes for each grid cell) is extended to examine changes in regional average temperature. Based on the results of the analysis of gridded data, we identify broad regions of West Africa encompassing many grid cells with similar seasonality in correlations between changes in local seasonal mean temperature and changes in global annual mean temperature and also between changes in local seasonal mean temperature and changes in local seasonal mean precipitation. For each region, we calculate seasonal mean regional average temperatures by averaging temperatures across all the grid cells in the broad region. We then plot changes in seasonal mean regional average temperature between 1986–2005 and 2081–2100 for each GCM against corresponding changes in annual mean global average temperature and calculate correlations across GCMs.

2.2. Results

2.2.1. Analysis of gridded data

We first examine how local temperature changes vary across the GCMs with their changes in global average temperature (using Eq. 1) by correlating changes in local seasonal mean temperatures with changes in annual mean global average temperatures across GCMs. Fig. 1 (column 1, the leftmost column) shows that local temperature changes near the Guinea Coast (i.e. in southern coastal West Africa) and the Sahara are strongly positively correlated with global temperature increases, meaning that, in general, GCMs with larger global average tempera-

ture increase tend to exhibit larger local temperature increases. From this, and our understanding of the global nature of anthropogenic warming, we can conclude that reducing uncertainties in projections of global average temperature is important for reducing uncertainties in temperature projections near the Guinea Coast and in the Sahara. In the Sahel, to the south of the Sahara, there is a zonal band of lower correlations. This is most evident in the July to September (JAS) wet season; the latitude and prominence of this band varies over the course of the year. This variation is reminiscent of the evolution of the West African Monsoon rains, so we next analyse correlations between local temperature change and local precipitation change.

Fig. 1. Results of linear regression of 39 GCM-simulated changes in local seasonal mean temperature (ΔT Local Seasonal) against corresponding changes in annual mean global average temperature (ΔT Global Annual) and local seasonal mean precipitation (ΔP Local Seasonal). Changes are between 1986–2005 and 2081–2100 in RCP8.5 simulations of 39 CMIP5 GCMs. Seasons are January to March (JFM), April to June (AMJ), July to September (JAS) and October to December (OND). The 2 leftmost columns (columns 1 and 2) show correlations between ΔT Local Seasonal and ΔT Global Annual (column 1) and between ΔT Local Seasonal and ΔP Local Seasonal (column 2). The remaining columns show the percentage of variance in ΔT Local Seasonal explained by variance in ΔT Global Annual and variance in ΔP Local Seasonal individually (columns 3 and 4) and in combination (column 5)

Fig. 1 (column 2) shows the inter-GCM correlations between local temperature change and local precipitation change (arising from Eq. 2). In all seasons except the January to March (JFM) dry season, local temperature changes are generally negatively correlated with local precipitation changes, and more so in the areas of West Africa where there are weaker correlations with changes in global average temperature. Strong negative correlations ($R < -0.6$) are most widespread in the JAS season, when the correlations with global average temperature are weakest. For most seasons of the year for most of West Africa, the CMIP5 RCP8.5 simulations show a mix of increases and decreases in seasonal mean precipitation during the 21st century (Biasutti 2013, IPCC 2013b, Rowell et al. 2016). The negative correlations between local temperature changes and local precipitation changes mean that GCMs with large increases (large decreases) in precipitation tend to have small (large) increases in temperature. Processes contributing to this could include rainfall moistening the soil and so reducing temperatures through increased surface evaporation and rain-bearing clouds shading the surface and so reducing temperatures through decreased surface insolation. This suggests that reducing uncertainties in projections of future changes in precipitation may be important for reducing uncertainties in temperature projections in the Sahel.

Fig. 1 also shows how the correlations translate to the inter-GCM variance in local seasonal mean temperatures explained by the change in annual mean global average temperature and local seasonal mean precipitation (columns 3 and 4). Where local temperature changes are strongly positively correlated with global temperature increase (near the Guinea Coast and in the Sahara; Fig. 1, column 1), the inter-GCM variance in global average temperature alone generally explains more than 60% of the inter-GCM variance in local temperature anomalies (Fig. 1, column 3). In contrast, $< 20\%$ of the variance in changes in local temperature is explained by the variance in changes in global average temperature alone across large parts of the Sahel in JAS. In this case, local temperature changes are negatively correlated with local precipitation changes (Fig. 1, column 2) and the variance in precipitation changes alone typically explain 20 to 55% of the variance in temperature changes (Fig. 1, column 4).

Results for the variance explained in the changes in local temperatures by the 2-variable linear regression model of change in global average temperature and change in local precipitation (Eq. 3) confirms the importance of changes in precipitation in some sea-

sons (Fig. 1, column 5). Overall, the variance explained by the combination of the variance in change in global average temperature and the variance in change in local precipitation is greater than the variance explained by the variance in change in global average temperature alone in JAS and, to a lesser extent, April to June (AMJ) and October to December (OND) (comparing columns 3 and 5 of Fig. 1). In these seasons, the 2-variable model explains at least 40% of the variance in changes in local temperature across almost all of West Africa, and mostly in excess of 60% in AMJ, JAS and OND. In JFM, the variance explained by the 2-variable model is similar to that explained by the variance in the change in global average temperature alone, which is unsurprising given the small amount of variance explained by the variance in changes in local precipitation in this season (Fig. 1, column 4).

2.2.2. Analysis of regional averages

Based on the patterns of correlations for local temperature changes in Fig. 1, we define 3 regions encompassing grid cells with similar behaviour. These are ‘Sahara’, ‘Western Sahel’ and ‘Guinea Coast’ (see top of Fig. 2). For each region, Fig. 2 shows changes in temperature averaged across all the grid cells in the region (making no distinction between land and sea grid cells in the case of Guinea Coast) plotted against corresponding changes in annual mean global average temperature.

Fig. 2 shows that, for all 3 regions, GCMs generally simulate changes in mean regional average temperature over the 21st century that are similar to or greater than corresponding changes in mean global average temperature. Furthermore, for the Sahara and Guinea Coast regions in all seasons, and for the Western Sahel in the dry JFM and AMJ seasons, inter-GCM correlations between regional and global warming values indicate that over 50% of the variance in regional warming is explained by the variance in global warming (i.e. the correlations are greater than 0.707). This statistical result, alongside a robust physical understanding (involving global advection of heat anomalies), informs the basis of our provision of refined probability distributions of regional temperature change in Section 3.

In contrast, Fig. 2 shows that correlations for the Western Sahel wet seasons are smaller, 0.49 for JAS and 0.67 for OND (consistent with Fig. 1), which we suggest may be due to a greater influence of future changes in precipitation via land-surface and/or

Fig. 2. Changes in seasonal mean regional average temperature against change in annual mean global average temperature for 3 regions: Sahara, Western Sahel and Guinea Coast. Seasons are as for Fig. 1. Changes are between 1986–2005 and 2081–2100 in RCP8.5 simulations of 39 CMIP5 GCMs. Correlations are given for both the full set of 39 GCMs and a set of 35 that excludes BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM (red triangles)

cloud effects. Furthermore, for JAS, 4 GCMs (BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM) show regional warming that is substantially less than the global average warming. Previous work notes substantial deficiencies in the ability of these GCMs to simulate the observed climate, and this casts doubt on whether their behaviour reflects that of the real world. For example, based on their failure to reproduce key aspects of the climate of Africa, Southeast Asia and Europe, McSweeney et al. (2015) regard climate projections from MIROC-ESM and MIROC-ESM-CHEM as ‘implausible’. A key observation made by McSweeney et al. (2015) in the context of this study is that the West African Monsoon flow is exaggerated in these GCMs relative to observations and other CMIP5 GCMs. There is less conclusive evidence supporting the implausibility of West African climate projections from BNU-ESM and FGOALS-g2. McSweeney et al. (2015) assess these GCMs as having ‘significant biases’ but the deficiencies noted in the models relate to the atmospheric circulation over Europe and, in the case of FGOALS-g2, the Southeast Asian Monsoon. The processes that lead to these deficiencies may or may not be relevant to the simulation of changes in the climate of West Africa, so rather than claiming definitively that BNU-ESM and FGOALS-g2 are unreliable in the context of West African temperature projections, we encourage further evaluation of these GCMs. Nevertheless, we find it instructive to assess the sensitivity of our correlation analysis to the exclusion of these GCMs, as well as MIROC-ESM and MIROC-ESM-CHEM. For the Western Sahel, the global–regional correlations increase to greater than 0.8 for JAS and OND. Disregarding these 4 GCMs makes little difference to the correlations for other combinations of regions and seasons. This suggests that the behaviour of processes that govern changes related to the incursion of the monsoon rains into the Sahel, and/or the intensity of the rains within the Sahel, is different in these GCMs than in the other 35. Nonetheless, the 35-GCM correlations between regional and global warming values for the wet seasons are still less for the Western Sahel than for the more northerly Sahara region and the more southerly Guinea Coast region, suggesting that changes in precipitation are still influencing the warming of the Western Sahel. If Fig. 1 is replotted without data from the BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM GCMs (see Fig. S1 in the Supplement), the spatial patterns are similar to those shown in the original Fig. 1. However, correlations between local temperature changes and local precipitation changes in the

Sahel in JAS and OND are less than with the full set of 39 GCMs. Consequently, a greater percentage of the variance in local temperature change is explained by the variance in global temperature change and a smaller percentage by the variance in local precipitation changes, again emphasising the anomalous behaviour of the BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM GCMs.

3. USING A GLOBAL WARMING PROBABILITY DISTRIBUTION TO REFINE PROJECTIONS OF REGIONAL WARMING

Each of the ensembles of CMIP5 RCP simulations typically used to develop climate projections for the 21st century does not fully sample uncertainties in future changes in global average temperature. Each ensemble is forced with a single prescribed trajectory of atmospheric carbon dioxide concentrations. Simulations of multiple RCPs can be used to sample uncertainties in carbon dioxide concentrations to some extent, but the simulations do not explicitly represent the response of atmospheric carbon dioxide concentrations to carbon dioxide emissions, including feedbacks due to the effects of climate changes on the carbon cycle (e.g. Bodman et al. 2016). This is because only approximately 20 of the CMIP5 GCMs include representations of both the oceanic and terrestrial carbon cycle and are able to simulate processes that partition carbon between the different components of the Earth system (e.g. uptake of carbon dioxide from the atmosphere by the ocean and vegetation) (see Table S1 and Flato et al. 2013). In addition, the sampling of uncertainty in the sensitivity of global average temperature to atmospheric greenhouse gas concentrations is limited to uncertainty related to model structure. Parametric uncertainty is not sampled. The GCMs incorporate a range of different algorithms to represent relevant processes (e.g. atmospheric convection, ocean transport processes related to the mixing of heat into the deep ocean), but each GCM uses only a single value for each uncertain parameter in the algorithms.

If the CMIP5 ensembles of future projections simulations under-sample uncertainties in future changes in global average temperature and there is a link between future changes in West African and global temperatures, as the results presented in Section 2 suggest, it follows that there is also an under-sampling of uncertainty in CMIP5-derived temperature projections for the region. Furthermore, the existence of such a link also suggests that more comprehensive

sampling of uncertainty in some published global average temperature projections could be translated to more comprehensive sampling of uncertainty in West African temperature projections. We therefore use this global–regional relationship—simply its existence rather than numerical data from it—to justify using a more robust distribution of global average temperature projections to refine projections of regional temperature change in West Africa. The following analysis demonstrates this for the regions shown in Fig. 2 for projections of temperature change between 1986–2005 and 2035–2064 under RCP8.5. Note that the future time period reflects the approximate time horizon of many long-term planning decisions, and differs from the 2081–2100 future period chosen to maximise the forced climate signal in Section 2.

3.1. Materials and Methods

3.1.1. Data

We use a probability distribution for the change in global average temperature from 1986–2005 to 2035–2064 developed for RCP8.5 by Murphy et al. (2018), hereafter the M18 distribution. This distribution has been constructed using a perturbed parameter ensemble (PPE) that accounts for uncertainties in the response of the climate to greenhouse gas emissions related to the carbon cycle and other key atmosphere, ocean and aerosol processes. The PPE comprises a large number of simulations of a computationally-inexpensive 2-box Simple Climate Model (SCM) that is forced by greenhouse gas emissions, and includes a representation of the carbon cycle that derives atmospheric carbon dioxide concentrations from emissions. The simulations within the ensemble differ in terms of values of key parameters in the carbon cycle equations and the equations that govern the effect of increases in atmospheric carbon dioxide concentration on the global mean surface air temperature. Parameter values for the simulations are chosen to maximise the sampling of uncertainty. To sample the uncertainty in the equilibrium response of global mean surface air temperature to a doubling of the atmospheric carbon dioxide concentration, values of relevant parameters are chosen to emulate the behaviour of a 280-member PPE of a configuration of the HadCM3 GCM with a 1-layer ocean representing the sub-surface mixed layer. Values of parameters associated with aerosol forcing, ocean heat uptake and the terrestrial carbon cycle, which determine the

speed of the response of global mean surface air temperature to increases in atmospheric carbon dioxide concentration and how these concentrations relate to emissions, are chosen to emulate the behaviour of a 57-member PPE of a HadCM3 configuration that includes the carbon cycle. To incorporate uncertainties related to model structure, simulations from CMIP5 are used to supplement both HadCM3 PPEs. In the final calculation of the distribution of global average temperature from the values simulated by the SCM PPE, each SCM simulation is weighted according to its ability to reproduce observationally-derived values of global average temperature, atmospheric carbon dioxide concentration and upper-ocean heat content for the recent past.

The M18 distribution improves the characterisation of uncertainty relative to ranges of likely change derived directly from an ensemble of structurally different GCMs with no systematic sampling of uncertainties in model parameters. However, Murphy et al. (2018) note that the distribution still relies on GCM simulations and so does not account for uncertainties due to processes not included in GCMs, and could be revised in the future based on improvements in climate modelling. However, our method is not dependent on this particular distribution, and it could be replaced in the future if improvements are made.

The M18 distribution and the CMIP5 GCMs give similar median values of change in global average temperature from 1986–2005 to 2035–2064 for RCP8.5 (1.64 and 1.66°C respectively). However, the M18 distribution has a broader range of likely warming values. The CMIP5 GCMs simulate changes in global average temperature of between 1.1 and 2.3°C for the mid-21st century, whereas the M18 distribution suggests a 17% likelihood of warming below this range and a 16% likelihood of warming above the CMIP5 range. Fig. 3 shows the resultant difference between the M18 probability distribution and a distribution fitted to the frequency distribution of the CMIP5 change estimates.

A factor that contributes to the breadth of the M18 distribution relative to the CMIP5 distribution in Fig. 3 is that the former is an ‘emissions-dependent’ projection and the latter is a ‘concentration-dependent’ projection. GCM-forcing datasets for RCP8.5 include both a time series of annual carbon dioxide emissions and a time series of annual atmospheric carbon dioxide concentrations (International Institute for Applied Systems Analysis [IIASA] 2009). The CMIP5 RCP8.5 simulations used here are forced with the time series of concentrations. However, the M18 distribution incorporates uncertainties in the carbon

Fig. 3. Derivation of the quantile mapping transformation showing (left) the comparison of global warming (GW) values simulated by CMIP5 GCMs (vertical black lines along x-axis and smooth black line) with a probability distribution of temperature anomaly between 1986–2005 and 2035–2064 in response to RCP8.5 from Murphy et al. (2018) and the transformed CMIP5 GW estimate (smooth coloured lines) once the quantile mapping process has been applied; and (right) cumulative probability distributions for the original CMIP5 GCM empirical, CMIP5 GCM interpolated and transformed interpolated CMIP5 GCMs, compared to Murphy et al. (2018)

cycle and is therefore conditional on the time series of emissions. Since there is uncertainty in how atmospheric carbon dioxide concentrations respond to these emissions, the M18 distribution corresponds to a range of different trajectories for concentrations, and not just the single trajectory used by the CMIP5 RCP8.5 simulations.

3.1.2. Method

To account for the additional uncertainty in projections of future temperature change in West Africa arising from the additional uncertainty sampled by the M18 distribution, we seek a process for transforming the global warming distribution derived from the CMIP5 GCMs to the M18 distribution. We can then apply the same transformation to distributions of CMIP5 regional warming, founded on our knowledge of a strong relationship between global and regional warming. We use a quantile mapping technique for producing the transformed regional warming estimates as follows:

(1) An Empirical Cumulative Distribution Function (ECDF) is derived from the global warming values simulated by the CMIP5 GCMs. This gives the probability that global warming is less than $x^\circ\text{C}$ as

$$P(x) = \frac{\text{Number of GCMs simulating global warming} \leq x}{\text{Total number of GCMs}} \quad (4)$$

Since this is only defined for global warming values simulated by a finite number of GCMs, the result is a stepped empirical cumulative distribution function (see Fig. 3, right-hand panel).

(2) A smooth Cumulative Distribution Function is derived from ECDF by linearly interpolating the CMIP5-simulated global warming values to 1000 global warming quantiles (i.e. global warming values are interpolated for the exceedance probabilities 0.1, 0.2, 0.3, ... 100 %). Values beyond the range of CMIP5 GCM estimates are extrapolated, assuming that the tails of the corresponding probability distribution function behave the same as the tails of a Gaussian CDF function.

(3) A transformation between the CMIP5 CDF and the M18 CDF is calculated. For each of the 1000 quantiles, q , a scaling factor, F_q , is calculated that maps the global warming value of the CMIP5 CDF, GW_q^{CMIP5} , to that of the M18 CDF, GW_q^{M18} :

$$GW_q^{\text{M18}} = F_q \times GW_q^{\text{CMIP5}} \quad (5)$$

Two sets of scaling factors are calculated—1 set for the full ensemble of 39 GCMs and 1 set for the ensemble that excludes the BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM GCMs. Scaling factors for 100 quantiles (1, 2, 3, ...100 %) are given in Table S2 in the Supplement.

(4) Quantiles of regional average warming are derived from the CMIP5 GCMs for each of the regions

shown in Fig. 3 for each of the seasons JFM, AMJ, JAS and OND using Steps (1) and (2) (i.e. by interpolating from an ECDF).

(5) The scaling factors derived in Step (3) are applied to the CMIP5-derived regional warming quantiles to produce regional warming probability distributions approximately consistent with the M18 global warming distribution.

An important assumption is that there is a strong correlation between changes in regional average temperature and changes in global average temperature. We believe that this is the case for West Africa, given the results presented in Section 2.2. However, Fig. 1 demonstrates that there are also secondary influences on changes in regional average temperatures. Unsurprisingly for the monsoon-dominated climate of West Africa, Section 2.2 showed a potential influence related to changes in local precipitation, which was shown to be larger for the Sahelian wet season.

Note also that a slight inconsistency arises in the application of the transformation to regional average temperatures because unforced climate variability is

larger on regional scales than for global average temperature. The scaling of the component of the differences in CMIP5 regional warming due to unforced variability therefore likely slightly overinflates the transformed range. However, calculations of the relative contribution of unforced variability to total uncertainty (see Rowell 2012 and Rowell et al. 2016) show that this is a small effect, especially for the Guinea Coast and Western Sahel.

3.2. Results

Fig. 4 shows ranges of likely change for regional warming between 1986–2005 and 2035–2064 from the raw (i.e. not transformed) and transformed CMIP5 regional warming distributions. Consistent with the headline global mean surface temperature change projections given by the IPCC's Fifth Assessment Report (IPCC 2013a), these are shown as 5th to 95th percentile ranges. Note that for the Western Sahel in JAS and OND, the distributions are developed using the

Fig. 4. Likely ranges and median values for transformed and raw probability distributions for changes in seasonal mean regional average temperature between 1986–2005 and 2035–2064 for RCP8.5. Seasons are as for Fig. 1. Data for the Murphy et al. (2018) and CMIP5 distributions for changes in annual mean global average temperature are also shown. *: distribution computed from a 35-GCM subset (see Section 2.2)

subset of 35 GCMs (i.e. consistent with the scaling factors given for 35 GCMs in Table S2) (see Section 2.2).

The transformation of the CMIP5 distributions does not greatly affect the median values of projected regional temperature change but increases the ranges of projected regional warming. In particular, the transformation introduces longer tails to the regional warming distributions (due to under-sampling by the CMIP5 GCMs of the tails of the M18 global warming distribution, see Fig. 3). For example, the transformed distribution for the Guinea Coast for the AMJ season has a 5th to 95th percentile range of 1.3 to 6.3°C, whereas the range for the corresponding raw distribution is 2.1 to 5.1°C.

4. DISCUSSION AND CONCLUSION

4.1. Consideration of uncertainties

One of the interesting dichotomies in climate science is the tension between the goal of reducing the uncertainty amongst climate models versus the requirement that the limitations of models be acknowledged and, in some cases, accounted for by increasing estimates of uncertainty beyond that expressed by standard model ensembles. This study has greater emphasis on the latter perspective but at the same time points towards routes for ultimately reducing uncertainty.

We have highlighted the high degree of correlation between future changes in West African temperature and future changes in global mean temperature in the CMIP5 GCM ensemble. We have demonstrated how, founded on this correlation and on the considerable research on the probability distribution of values for future global warming, a quantile-quantile mapping scheme can be used to translate CMIP-derived regional temperature projections into more defensible probability distributions of future regional temperature change. The outcome is a set of distributions that account for sources of uncertainty in global warming that are not well characterised by the CMIP5 future projections ensembles. These include:

- Carbon cycle uncertainties: The GCM simulations comprising most of the CMIP5 future projections ensembles do not represent the carbon cycle, and so the partitioning of carbon between the atmosphere and other components of the Earth system (e.g. due to carbon dioxide exchanges between the atmosphere and oceans, and between the atmosphere and terrestrial biosphere) is not represented. Uncertainty in the response of atmospheric carbon dioxide con-

centrations to carbon dioxide emissions, and consequent uncertainty in global mean temperature, are therefore not fully sampled by the CMIP5 future projections ensembles (e.g. Bodman et al. 2016). The use of the M18 distribution in our method allows carbon cycle uncertainties to be sampled, within the constraints of the GCM simulations and methodology used in its construction

- Climate sensitivity: Structural differences between the CMIP5 GCMs give rise to different simulated magnitudes for the increase in global mean temperature in response to a given increase in atmospheric carbon dioxide concentration (e.g. a doubling of carbon dioxide concentration) (Flato et al. 2013). However, there is no systematic sampling of parametric uncertainty in the sensitivity of the climate system to increases in concentrations by the CMIP5 future projections ensembles. The use of the M18 distribution in our method improves the sampling of uncertainty in global climate sensitivity by also sampling uncertainties in key parameters (e.g. related to atmospheric aerosols and ocean heat uptake)

However, we note that the temperature distributions produced by our method do not account for all uncertainties in future changes in regional climate. Sources of uncertainty that are not accounted for include:

- Unsampling parametric uncertainty: Our method does not account for parametric uncertainties that could affect the links between global and regional warming and how these links could change due to climate change (e.g. related to changes in the large-scale circulation of the atmosphere or the coupling of local temperatures to soil moisture)

- Common deficiencies in GCMs: Common deficiencies in GCMs could be leading to an under-sampling of uncertainty by both the M18 distribution and the CMIP5 ensemble. For example, Murphy et al. (2018) note that contemporary GCMs have an erroneous additional moisture convergence zone in the southwest Pacific (e.g. Tian & Dong 2020), and omit relevant known processes, such as the release of greenhouse gases from permafrost and ocean sediments (Collins et al. 2013), and potentially others not currently known to us

4.2. Implications for climate change impact assessments

Because of the incorporation of carbon cycle uncertainties and better sampling of uncertainty in global climate sensitivity, our method gives regional warm-

ing distributions with longer tails than distributions estimated directly from the CMIP5 ensemble. This is an important result, as it suggests that assessments of climate change impacts in West Africa that are sensitive to temperature may underestimate the probability of large (and small) impacts if they use climate projections derived directly from the ensembles of CMIP5 RCP simulations. However, from the perspective of planning for climate change impacts, the refined projected ranges of likely regional warming are very large. For example, the likely range of warming for the Western Sahel for the AMJ season is 2.0 to 7.3°C, and there is a 10% chance of warming outside this range. However, an alternative to expressing the distributions in terms of a likely range that may be more informative for adaptation planning is to consider the implied risk of temperature changes beyond critical thresholds. The usefulness of this framing is supported by previous research suggesting that there are critical warming thresholds for key sectors in West Africa. For example, Sultan et al. (2013) found a consistent decrease in simulated yields of staple crops in a region roughly corresponding to our Western Sahel region when projected future summer mean temperatures warmed to greater than 2°C above their 1961–1990 average. We use a different baseline period for our projections (1986–2005) and analyse different seasons than Sultan et al. (2013). However, we note that, compared to warming distributions derived from raw CMIP5 data, our transformation either does not change or decreases the chance of a greater than 2°C warming in seasonal mean temperatures in all of the regions and seasons that we have analysed. The most extreme result is a decrease in the chance of warming exceeding 2°C from 87 to 67% for the Sahara in the OND season. However, there are increases in the chance of warming exceeding 3°C in some regions and seasons. The most extreme result is a 5-fold increase in the chance of warming exceeding 3°C from 5 to 25% for the Western Sahel in the OND season.

4.3. Advantages of the method

The approach taken to generating these projections is potentially valuable for 2 main reasons. Firstly, in contrast to projections derived from data solely from CMIP GCMs, or dynamically downscaled from them, the transformation allows information on uncertainties that are not well represented by CMIP ensembles, including observational constraints, to be incorporated into the regional warming projections.

This goes some way to addressing the limitation of GCM-derived projections for climate change risk assessment in that they do not account for the full range of uncertainty in future climate changes (e.g. Brown & Wilby 2012). Our method allows information on uncertainties in global warming beyond that represented by CMIP ‘ensembles of opportunity’ (e.g. from PPEs of simpler GCMs designed to sample uncertainty and observational constraints) to inform regional warming projections. These uncertainties include uncertainties in the carbon cycle, which, when accounted for, can give significantly different likely ranges for future increases in global average temperature than those from CMIP (e.g. Bodman et al. 2016).

Secondly, the scientific effort being devoted to refining projections of global average temperature is substantial, with observational constraints and expert judgement being brought to bear to complement climate modelling. The refined projections of future regional temperature change that we have generated have larger uncertainties than projections derived directly from the CMIP5 ensemble. Further work to reduce uncertainties in global, or regional, temperature projections is beyond the scope of this study. However, if reductions in the uncertainty in global average temperature projections are achieved, the approach that we have demonstrated provides a simple, effective and resource-efficient means to immediately translate these into reductions in the uncertainty in temperature projections for West Africa to the benefit of its communities. Prospects for such a reduction in uncertainty depend on reducing uncertainties in future concentrations of greenhouse gases in the atmosphere, and the global climate sensitivity to those concentrations. Numerous factors combine to determine changes in global average temperature, including feedbacks in the climate system, such as those related to polar albedo and clouds, feedbacks in the carbon cycle and the effects of atmospheric aerosols; all the subject of ongoing research on reducing uncertainty (e.g. Myhre et al. 2015, Stevens et al. 2016, Armour 2017, Booth et al. 2017).

4.4. Broader applicability of the method

The reliance of our method on correlations between future changes in West African temperature and future changes in global mean temperature has implications for its wider applicability. Firstly, many local climate variables, including precipitation, are

not as closely linked to global mean temperature as local mean temperature (e.g. Rowell 2012, Tebaldi & Arblaster 2014, Sutton et al. 2015). Our approach may be less applicable to these variables. However, noting the scaling of temperature extremes with global mean temperature (Seneviratne et al. 2016), it likely has some applicability to temperature extremes as well as mean temperatures. Secondly, the source of the correlations lies in the forced response of the GCMs. The unforced variability in local temperatures is often not correlated with global average temperature (e.g. Sutton et al. 2015). Hence our approach is not appropriate for climate timescales or regions that are strongly influenced by unforced variability (e.g. projections for the next decade). We reiterate, however, that Rowell et al. (2016) showed only a small contribution of unforced variability to uncertainties in CMIP5-based projections of 20 year mean temperatures for 2041–2060 for West Africa. Thirdly, the response of regional temperature to changes in global average temperature changes with time in some specific situations, and this also renders our method inappropriate. For example, Tebaldi & Arblaster (2014) note that the relationship between local and global temperature changes can vary in time near the edge of melting polar ice caps, due to changes in surface albedo, or in scenarios in which global average temperatures begin to stabilise, due to the equilibration of deep ocean temperatures.

4.5. Recommendations for further work

There is scope for future research to build on our approach to further refine projections of future temperature change in West Africa. For example, noting that the strength of the correlations for the Western Sahel wet season are contingent on excluding the BNU-ESM, FGOALS-g2, MIROC-ESM and MIROC-ESM-CHEM GCMs, further work assessing the reliability of these is recommended. We have demonstrated that the behaviour of these GCMs is anomalous for the Sahel for these seasons (see Section 2.2) and other studies (e.g. McSweeney et al. 2015) call the reliability of the MIROC-ESM and MIROC-ESM-CHEM GCMs into question. We particularly recommend further evaluation of the BNU-ESM and FGOALS-g2 GCMs. In addition, relationships between changes in local temperature and changes in climate variables other than global average temperature, especially local precipitation, could be further explored. Our results showing the potential influence of precipitation in the Sahelian wet season suggest that projected

changes in local precipitation could be used to further refine projected changes in temperature for West Africa.

Finally, we suggest that our method could be used to refine temperature projections for the many other regions of the world in which regional temperature changes are highly correlated with global mean temperature changes.

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