African Climate Change Uncertainty in Perturbed Physics Ensembles: Implications of Global Warming to 4°C and Beyond*

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ABSTRACT

The importance of investigating regional climate changes associated with degrees of global warming is increasingly being recognized, but the majority of relevant research has been based on multimodel ensembles (MMEs) from the Coupled Model Intercomparison Project (CMIP). This has left two important questions unanswered: Are there plausible futures which are not represented by the models in CMIP? And, how would regional climates evolve under enhanced global warming, beyond 4°C? In this paper, two perturbed physics ensembles (PPEs) are used to address these issues with reference to African precipitation. Examination of model versions that generate warming greater than 4°C in the twenty-first century shows that changes in African precipitation are enhanced gradually, even to high global temperatures; however, there may be nonlinearities that are not incorporated here due to limited model complexity. The range of projections from the PPEs is compared to data from phases 3 and 5 of CMIP (CMIP3 and CMIP5), revealing regional differences. This is partly the result of implausible model versions, but the PPE dataset can be justifiably constrained given its size and systematic nature, highlighting an additional advantage over MMEs. After applying constraints, the PPEs still show changes that are outside the range of CMIP, most prominently strong dry signals in west equatorial Africa and the Sahel, implying that MMEs may underestimate risks for these regions. Analysis of African precipitation changes therefore demonstrates that regional assessments that rely on CMIP3 and CMIP5 may overlook uncertainties associated with model parameterizations and pronounced warming. More systematic approaches are needed for conservative estimates of danger.

1. Introduction

For two decades, politicians have been debating temperature limits to which anthropogenic global warming should be restricted, and 2°C has emerged as a benchmark for danger (e.g., UNFCCC 2010). Yet there is very little scientific evidence with which to judge whether 2°C,

or any other degree of warming, would be safe from a regional perspective. The need for regional assessments at specific degrees of global mean temperature increase (ΔT_g) is increasingly being recognized (e.g., May 2008). James and Washington (2013, hereafter JW13), highlight the importance of such research for Africa, a continent highly vulnerable to changes in water availability (Boko et al. 2007), and present local precipitation changes associated with 1°, 2°, 3°, and 4°C of ΔT_g . However, JW13, like the majority of existing climate projection research, is based on data from phase 3 of the Coupled Model Intercomparison Project (CMIP3).

CMIP3, and the succeeding phase 5 of CMIP (CMIP5), are multimodel ensembles (MMEs): “ensembles of opportunity” that result from organized experiments at many international modeling centers. Each model has been created separately using different resolutions and parameterization schemes (Collins 2007). In contrast,

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perturbed physics ensembles (PPEs) consist of many versions of the same base model: parameter values are varied to examine the uncertainty in future climate resulting from processes that are poorly represented in models such as convection. Using PPEs has two potential benefits in an investigation of global warming: they offer the opportunity to explore global temperatures beyond 4°C, and to better understand modeling uncertainty.

Investigating large greenhouse gas (GHG) forcing is imperative for mitigation: the costs and benefits of a 2°C global temperature target can only be appreciated with reference to the consequences of unmitigated anthropogenic interference. If mitigation is unsuccessful, research into higher levels of radiative forcing could also provide information for adaptation. Without mitigation, global warming could greatly exceed 2°C: CO₂ emissions are continuing to rise, and the sensitivity of the climate system to this forcing is uncertain. Some models generate warming >7°C for a doubling of CO₂ (Murphy et al. 2004; Stainforth et al. 2005). Accordingly, there has been an emphasis on impacts assessment at 4°C and beyond, including several conferences (e.g., in Oxford in 2009). However, twenty-first-century projections beyond 3°C are not widely available, due to the combination of GHG forcing and model sensitivity in CMIP. Much of the relevant research has relied on pattern scaling to investigate higher degrees of warming (e.g., Thornton et al. 2011), assuming a linear relationship between ΔT_g and local climate. Experts suggest that the response to warming may be nonlinear, and there could be tipping points in the Earth system, which are more likely to be reached at higher global temperatures (Kriegler et al. 2009). Direct investigation of 4°C and beyond is therefore a priority. PPEs offer the potential to address this challenge, since the perturbation of parameter values can generate a large range of climate sensitivities (e.g., Stainforth et al. 2005).

PPEs might also be useful for investigating modeling uncertainty at each ΔT_g interval. The importance of consulting multiple models in climate change assessments is widely recognized. Many projection papers (e.g., Giannini et al. 2008) and impacts studies (e.g., Thornton et al. 2011) have sought to compare results from different models, and have employed data from CMIP toward this end. However, using MMEs to illustrate the range of possible futures is problematic. It is difficult to evaluate whether any of the projections within this range are implausible; and there may be other plausible futures that are not represented, as each model is designed to fit twentieth-century conditions, and different models often share data and algorithms (Allen and Ingram 2002). PPEs explore uncertainty

more systematically, making it easier to evaluate individual model versions, and to investigate whether differences in model physics produce different responses. PPEs developed by the Met Office Hadley Centre (MOHC; Murphy et al. 2007) and climateprediction.net (Stainforth et al. 2005) capture much of the uncertainty of MMEs (Webb et al. 2006; Rowell 2012) and enlarge the range of projections for some variables (Fung et al. 2011; McSweeney et al. 2012).

The aim of the present study is to reexamine the implications of global warming for African precipitation, using two MOHC PPEs to investigate the development of change to 4°C and beyond and assess the extent to which parameter perturbations broaden the range of potential futures from CMIP3 and CMIP5 at each ΔT_g interval. A smaller PPE of coupled models is used to explore higher degrees of warming and make quantitative comparisons to CMIP, while a much larger ensemble of slab models enables analysis of the variability in local precipitation responses resulting from a wide range of parameter combinations, and the extent to which specific parameter values produce unrealistic simulations. These datasets are described in the next section, followed by an outline of the tools used to explore projections in each. In section 4, local precipitation projections at 1°–6°C of ΔT_g are presented. Then checks for implausible signals in the largest ensemble are described, before projections from both PPEs are compared to CMIP3 and CMIP5. The implications of these results are discussed with reference to research and policy, and conclusions follow.

2. Data

Four ensembles of global climate models (GCMs) are used here: two CMIP MMEs, CMIP3 and CMIP5; and two MOHC PPEs, one consisting of 280 slab models [atmosphere–slab model PPE (AS-PPE)] and the other of 17 coupled models [atmosphere–ocean model PPE (AO-PPE)].

a. CMIP MMEs

Monthly twenty-first data were selected from CMIP3 (Meehl et al. 2007) and CMIP5 (Taylor et al. 2012) for all models accessible in the highest widely available forcing pathway: 19 CMIP3 models run in the Special Report on Emissions Scenarios (SRES) A2 scenario (see Table 1 in JW13), and 37 CMIP5 models run in the representative concentration pathway (RCP) 8.5 (see Table S1 in the supplemental material). Twentieth-century data from “20C3M” (CMIP3) and “historical” (CMIP5) experiments were obtained for the same models.

One realization was used per model. Data were interpolated to a $1^\circ \times 1^\circ$ spatial resolution.

b. Atmosphere–Slab Model PPE

AS-PPE (Rougier et al. 2009) is based on the Hadley Centre Slab Climate Model, version 3 (HadSM3), which has the same atmospheric and land surface physics as the Hadley Centre Coupled Model, version 3 (HadCM3, one of the coupled models in CMIP), but with a 50-m mixed layer or “slab” ocean. To investigate uncertainty in future climate, 31 atmospheric and land surface parameters were perturbed from the parameterization schemes for large-scale cloud, convection, radiation, sea ice, boundary layer and surface processes, and dynamics, producing 280 model versions (Barnett et al. 2006). Each ensemble member was run in two equilibrium experiments forced by preindustrial and doubled CO_2 ($2 \times \text{CO}_2$). The runs continue for 20 years beyond equilibrium and 20-yr monthly means from this period were the basis for analysis. These data have a spatial resolution of 2.5° latitude and 3.75° longitude.

c. Atmosphere–Ocean Model PPE

The base model for AO-PPE (Murphy et al. 2007) is HadCM3: the same as in CMIP except with flux adjustments and an interactive sulfur cycle. HadCM3 has an atmospheric resolution matching HadSM3, coupled to a fully dynamical ocean. Because of the greater computational expense it was not possible to run all 280 atmospheric configurations from AS-PPE with the coupled model; therefore 17 versions were chosen. As well as the standard model, the variant with the best simulation of present-day climate was used, and 15 others were selected to span a range of climate sensitivities and parameter values (Collins et al. 2011). Monthly data were selected from transient experiments: a control run with preindustrial forcings, and the high emissions scenario SRES A1FI (Betts et al. 2011). For the control a 20-yr reference period was selected 40 years into the run to avoid spinup issues.

3. Methods

Changes in precipitation associated with global warming were calculated for all ensembles. The AS-PPE experiments have a fixed level of anthropogenic forcing ($2 \times \text{CO}_2$), and climate sensitivity and local precipitation responses to $2 \times \text{CO}_2$ were computed for each ensemble member. CMIP3, CMIP5, and AO-PPE are run in transient scenarios, with increasing global temperature over time, allowing local changes to be analyzed as a function of global temperature: in the case of AO-PPE, up to 6°C .

a. Deriving global mean temperature change (ΔT_g)

For each member of AS-PPE, the global mean temperature change associated with $2 \times \text{CO}_2$, or climate sensitivity, was derived from 20-yr annual mean 1.5-m temperature data. Data were first weighted by gridbox area.

For the transient ensembles (AO-PPE, CMIP3, and CMIP5), local precipitation change was analyzed at 1°C intervals of ΔT_g . To find the time of each ΔT_g interval, ΔT_g time series were created for each model as follows. Annual mean temperature data (1.5 m for AO-PPE and near surface for CMIP3 and CMIP5) were weighted by gridbox area and global averages were calculated for control (preindustrial for AO-PPE and twentieth century for CMIP3 and CMIP5) and forced (A1FI for AO-PPE, A2 for CMIP3, and RCP8.5 for CMIP5) time series. Each year in the twenty-first century was differenced from a 15-yr control climatology. The period 1985–99 was used for CMIP3 and CMIP5, which differs from the preindustrial reference referred to in policy, but previous work shows results are robust to changes in the baseline (JW13).

The ΔT_g time series were smoothed using polynomial regression (all r^2 values >0.97) and the year each 1°C interval of ΔT_g was reached was extracted and defined as the median of a 15-yr period, to be used to analyze local precipitation change. The 15-yr sample length was designed to eliminate interannual variability and to dampen multidecadal variability. The number of ΔT_g levels available varies between models, and is a maximum of 3°C for CMIP3, 5°C for CMIP5, and 6°C for AO-PPE (see Table S2 in the supplemental material).

b. Local changes in precipitation

Precipitation anomalies associated with anthropogenic forcing ($2 \times \text{CO}_2$ for AS-PPE and ΔT_g samples for AO-PPE, CMIP3, and CMIP5) were calculated on a model grid point by grid point basis for each ensemble member, for the annual mean and eight seasons—December–February (DJF), March–May (MAM), June–August (JJA), September–November (SON), January–March (JFM), April–June (AMJ), July–September (JAS), and October–December (OND)—since precipitation seasonality in Africa is regionally specific. Gridded anomalies were tested at a significance level of 5% using non-parametric tests, as precipitation has a skewed distribution in many arid regions. For all four datasets a Wilcoxon signed-rank test was used (following Wilks 2006) to establish whether the ensemble shows significant positive or negative change distinct from variation between models. The control and forced climatologies for each ensemble formed pairs in the sample. For CMIP3, CMIP5,

FIG. 1. Ensemble mean seasonal precipitation anomalies (mm day^{-1}) associated with 1° , 1.5° , 2° , 3° , 4° , 5° , and 6°C of ΔT_g in AO-PPE. Grid points where $<66\%$ of models agree on the direction of change are masked in white, and grid points where $>80\%$ of models agree on the direction of change are stippled. Grid points where $>80\%$ of models show no significant change are shown in gray.

and AO-PPE the Mann–Whitney U test was also employed to test whether individual models show significant change relative to interannual variability (as in James et al. 2013). This test was not applied to AS-PPE as interannual data were not readily available.

4. Evolution of regional changes with 1° – 6°C global warming

Because of the combination of high GHG forcing (SRES A1FI) and model sensitivity, some members of AO-PPE generate warming greater than 4°C in the twenty-first century. By investigating changes from 1° to 6°C in this ensemble, the extent to which a group of coupled models shows gradual or nonlinear change in African precipitation with higher degrees of global warming is examined here for the first time. Changes at 1.5°C are also presented because of the consideration of this level in policy (UNFCCC 2010).

Precipitation projections exhibit spatial, seasonal, natural, and intermodel variability. Here we show four seasons of relevance to regional precipitation and present an overview of the most dominant responses in AO-PPE (Fig. 1) by displaying the ensemble mean, but only where there is intermodel agreement in the direction of change, and not for grid points where there is a lack of signal relative to interannual variability (shown in gray) or a lack of consensus as to whether conditions would be wetter or drier (shown in white). This is not designed to provide information about risks associated with each degree of warming, as the magnitude of response varies substantially between models, some of which illustrate the risk of considerably larger responses. Furthermore, the significance test used here is conservative given the small sample size (15 yr); therefore, even where all models show a lack of signal, there might still be changes that would be measured to be significant were a longer time period to be used. So rather than

allowing for risk assessment, the figure is intended to illustrate how precipitation patterns develop on average as global temperature increases. Note that the ensemble mean is calculated using the models available at each degree of ΔT_g (see Table S2), meaning that some differences between ΔT_g intervals are due to the inclusion of different models rather than change in global temperature, but the development of local change with ΔT_g in individual models has also been considered (not shown).

At 1°C of ΔT_g , most models experience a lack of significant change (shown in gray) across much of the African landmass. This does not imply that changes at 1°C are unimportant; for example, there may be shifts in extremes. Rather it demonstrates the lack of change in the seasonal mean, in contrast to higher degrees of warming. At 1.5°C there are significant decreases in seasonal mean precipitation of $>10\%$ in parts of southern and western Africa. At 2°C these anomalies are strengthened and extended, and there are additional changes in central Africa. By 3°C the ensemble mean shows drying throughout much of western Africa during JAS: $>20\%$ in the Sahel and the Congo basin. In SON, negative anomalies stretch across most of southern Africa, meridionally opposed to a band of positive anomalies to the north of the equator, which extends into East Africa, implying a strengthening of the “short rains” season and an increased likelihood of flooding.

At 4°C and beyond there are some new signals, particularly wetting at the Guinea Coast during DJF, but the main transformation from 3° to 6°C is an increase in the spatial coverage of the anomalies and their amplitude. Southern Africa provides a typical example: the ensemble average drying during SON is $>10\%$ at 3°C and $>40\%$ at 6°C . Individual models also show approximately linear amplification of precipitation change with ΔT_g . AO-PPE therefore suggests gradual enhancement of local precipitation changes with global warming: the main difference between ΔT_g intervals is in the strength and extent of anomalies, rather than in the direction or rate of change.

5. Comparing projections from PPEs and MMEs

AO-PPE and AS-PPE have been created by running the same base model multiple times with different parameter values. They explore uncertainty, and can be used to test the range of projections produced using CMIP3 and CMIP5. The two PPEs contribute to this evaluation differently. AO-PPE consists of coupled models run in transient experiments, as in CMIP, allowing for quantitative comparison of the range of projections. However, AO-PPE has relatively few members, meaning

there is also value in using slab model experiments from AS-PPE. These equilibrium simulations are not directly comparable to the transient runs, since it is not possible to examine the evolution of change with warming, and local precipitation responses to radiative forcing may be different on longer time scales (Chou and Neelin 2004). AS-PPE is nevertheless useful because of its many ensemble members, allowing investigation of the influence of a greater number of parameter combinations on the range of precipitation projections and also allowing investigation of the extent to which the simulations that produce this range are credible. Before comparing projections from all four ensembles we investigate variability within AS-PPE to determine whether any ensemble members should be judged as implausible and hence eliminated.

a. Applying constraints to a large PPE

AS-PPE consists of many model versions, the differences among which are well understood. This allows modes of variability to be identified and reasons for variability to be diagnosed. This is particularly important given that the last of the three stages of development for AS-PPE (Webb et al. 2006; Murphy et al. 2004; Rougier et al. 2009) was intended to explore parameter space rather than produce realistic climates. The ensemble was previously constrained by Sexton et al. (2012), who produced probabilistic projections using a multivariate Bayesian framework combining information from AS-PPE, CMIP3, and observations. Here we opt for a simpler approach, which focuses on African precipitation and allows for a more specific understanding of the causes of variability. This is informed by and is complementary to Sexton et al.’s framework.

Empirical orthogonal functions (EOFs) were calculated to identify dominant modes of variability, in terms of precipitation, and also separately for temperature at 1.5 m because of its strong control on precipitation. The analysis was conducted for the global tropics (40°N – 40°S) to assess African variability in a large-scale context, and for both climatologies and anomalies associated with $2 \times \text{CO}_2$, to identify variability in the background climate and in the response to anthropogenic forcing. The EOFs were computed from covariance matrices of grid boxes versus ensemble members (similar to Sanderson et al. 2008). The resulting EOFs represent the major spatial patterns of intermodel variability across AS-PPE, and principal components (PCs) illustrate the amplitude of the EOF in each ensemble member.

Several of the EOFs revealed large differences between model versions over Africa, in terms of precipitation climatologies, and temperature and precipitation changes associated with $2 \times \text{CO}_2$. The relationship between the

strength of the corresponding PCs and different components of the model physics was investigated across the 280 model versions to diagnose the causes of intermodel variability and to establish whether this likely results from limitations in our understanding of climate modeling or from identifiable model errors, and therefore whether the ensemble can be constrained based on existing knowledge.

1) CONSTRAINT BASED ON PRECIPITATION CLIMATOLOGIES

The first mode of variability in precipitation climatologies (EOF1; Fig. 2a) shows a strong contrast between land and ocean. This pattern is also evident when the EOFs are rotated using varimax rotation, and the North test (North et al. 1982) suggests it is an independent mode. It continues to dominate variability after CO₂ doubling. Land–ocean contrast is therefore a pervasive signal in the dataset. Model versions with the largest positive amplitudes for EOF1 have dry continents and wet oceans relative to the ensemble mean, with precipitation <1000 mm yr⁻¹ throughout the African continent. Despite uncertainty in precipitation climatologies for some African regions (Washington et al. 2013), it seems clear that this is too dry; for example, African rain forests require approximately 1500 mm yr⁻¹ (Malhi et al. 2009).

A composite of ensemble members with dry continents and wet oceans [high first PC (PC1)] was investigated further to identify reasons for this pattern. These models belong to the third part of the ensemble (Fig. 2b), intended to explore interactions between parameterizations rather than produce realistic models (Collins et al. 2011). They are also the same model versions that Sexton et al. (2012) found to dominate variability in AS-PPE when eigenvector analysis was conducted using 12 variables and multiple seasons. The amplitude of the first eigenvector from their analysis is negatively correlated with PC1 ($r^2 = 0.88$). Sexton et al. (2012) found this mode to be controlled by heat convergences: the heat sources that are added to slab oceans to simulate heat transport and correct for top of atmosphere (TOA) flux imbalances. Different heat convergences are calculated for each model version during calibration (Collins et al. 2011). Here we find that models with dry continents and wet oceans (large PC1 values) have a large negative TOA flux imbalance (meaning there is more outgoing than incoming radiation) and positive heat convergences. There is a strong correlation between TOA flux imbalance and PC1 across the ensemble ($r^2 = 0.86$; Fig. 2b).

This can be understood physically. The negative radiative imbalance will have a cooling effect over land, but over the oceans it is offset by the heat convergence.

FIG. 2. (a) A map of EOF1 for the AS-PPE control annual mean precipitation climatologies, and (b) the relationship between the amplitude of this mode and TOA flux imbalance. The EOF has been weighted in order to give a correlation score (r) as the EOF loadings, where $r = 100[u/(v)^{1/2}]$, where u is the eigenvector and v is the eigenvalue. The thicker black contour represents 0 with other contours at intervals of 0.05. Areas with positive (negative) values are distinguished by solid (dashed) contours and a white (gray) background. Cross hatching indicates $r < -0.15$. In (b) the different triangles represent the first (light gray), second (gray outline), and third (black) stages in which the ensemble was created.

Because of the tendency toward a constant ratio of temperature change over land and ocean (e.g., Joshi et al. 2007), heat will be transported from ocean to land, with associated changes in circulation (Lambert et al. 2011). The heat added to the oceans promotes evaporation, precipitation, and convection, while there is anomalous subsidence and drying over land. The precipitation climatology is therefore unrealistic, and a constraint was applied to the ensemble to remove the 140 model versions with TOA imbalances $>5 \text{ W m}^{-2}$, corresponding to the estimated observational uncertainty in this value (Collins et al. 2011; Rowlands et al. 2012).

2) CONSTRAINT BASED ON CHANGES ASSOCIATED WITH $2 \times \text{CO}_2$

Of the modes of variability in changes associated with $2 \times \text{CO}_2$, EOF2 for precipitation change (Fig. 3a) and EOF3 for temperature change (Fig. 3b) have the clearest signals over Africa, most prominently the

Congo basin. The patterns persist when the EOFs are rotated, and are shown to be independent using the North test. Model versions with large amplitudes for these modes project strong drying and warming of central Africa, as well as Amazonia. These ensemble members were explored further to assess the plausibility of this potentially dangerous response. Analysis of the difference in parameter values between ensemble members with high and low PC values revealed that models with a pronounced warming and drying response in the Congo have low entrainment coefficients, meaning there is little mixing of air with the surrounding environment in convective plumes. Composites of model versions with entrainment coefficients <2 show a similar response (Figs. 3c,d).

Previous work has shown low entrainment to be unrealistic (Rodwell and Palmer 2007), and Sexton et al. (2012)'s analysis based on observational constraints reveals that the likely range is much smaller than the expert specified range used in the design of AS-PPE. Following their probability estimates, we remove ensemble members with entrainment coefficients <2 and >4 , leaving a subensemble of 112. This constraint greatly reduces variability between model versions in terms of temperature and precipitation change associated with $2 \times \text{CO}_2$, particularly over the Congo basin (Fig. 4). There is still variability between members of the subensemble; however, we did not find any other implausible signals, and therefore this group of model versions will be used to make comparisons with AO-PPE and CMIP. AO-PPE also contains four model versions with entrainment coefficients >4 and these have been removed for the remainder of the analysis, leaving 13 members. Note that Fig. 1 is very similar when produced using only these model versions (not shown).

b. Comparing constrained PPEs with MMEs

The AS-PPE and AO-PPE subensembles are now compared with CMIP3 and CMIP5 to assess whether systematic parameter perturbations produce precipitation projections that are not represented by the CMIP "ensembles of opportunity." The most important comparison is in the range of projected futures; however, this is difficult to display on a continental scale, and therefore we first present ensemble mean projections to give an overview of the dominant responses to global warming in each dataset and to provide a context for comparing the ranges of projections, which is then done on a regional basis.

It is important to note that in each ensemble some projections are likely to be more credible than others. This remains true for the PPEs, as there may be implausible versions other than those identified above, and also for

the MMEs, which we do not attempt to constrain here given the difficulties involved (this will be discussed further in section 6b). Many of the differences between datasets may therefore be due to model error, but until physically based methodologies are developed to defensibly constrain the ensembles further it is conservative to include all models that have not been identified to be implausible, and this section is intended to examine whether there are differences between the datasets on this basis.

1) DIFFERENCES IN ENSEMBLE MEAN RESPONSE

Figure 5 shows dominant precipitation responses in each ensemble. For AS-PPE these are ensemble mean anomalies associated with $2 \times \text{CO}_2$, for grid points where change is significant relative to variation between ensemble members. For AO-PPE, CMIP3, and CMIP5 the rate of change in local precipitation per degree Celsius of global warming is presented. This was calculated by linearly regressing local precipitation anomalies against global temperature (ΔT_g) using ordinary least squares. The slope of the regression line (m) represents local change per degree Celsius of ΔT_g , where data points are overlapping 20-yr time periods: global temperature anomalies and local precipitation anomalies associated with 2000–19, 2010–29, etc., relative to control climatologies (20-yr preindustrial for AO-PPE and 1980–99 for CMIP3 and CMIP5). The baseline was not included as a data point, meaning the results are insensitive to the reference climatology, allowing for direct comparison of AO-PPE, CMIP3, and CMIP5. For each model, the significance of the slope was tested for difference from zero using a t test, following Wilks (2006), at a significance level of 5%. The figures show the ensemble mean slope. The percentage of models with a significant slope was calculated for each grid box, and areas where the models agree on a lack of significance are shown in gray. The percentage of positive slopes was also computed, and areas where the models disagree in the direction of change are shown in white.

Using Fig. 5 it is possible to make a qualitative comparison of the main wetting and drying responses across all four datasets and a quantitative comparison between the rates of change associated with warming in AO-PPE and the CMIP MMEs. As noted elsewhere (e.g., Knutti and Sedlacek 2013), the precipitation response is very similar in CMIP3 and CMIP5. There are also similarities in the pattern of change across all of the ensembles. The most consistent precipitation signals are the wet response in East Africa and drying in southern Africa during SON. However, there is variation between the datasets in the intensity and spatial extent of these anomalies. The equatorial wet signal in SON has

FIG. 3. Maps of (a) EOF2 for precipitation change and (b) EOF3 for temperature change for AS-PPE. Maps of annual mean (c) precipitation and (d) temperature anomalies associated with $2 \times \text{CO}_2$ for composites of all model versions with entrainment coefficients < 2 . In all except (d) the thick black contour represents 0. In (a) contours are at intervals of 0.2 and areas with positive (negative) values of r are distinguished by dashed (solid) contours and a gray (white) background. Cross hatching indicates $r > 0.3$. In (b) contours are at intervals of 0.2 and positive (negative) values are distinguished by solid (dashed) contours and a white (gray) background. Cross hatching indicates $r < -0.8$. In (c) contours are at intervals of 0.4 mm day^{-1} and wetting (drying) regions are distinguished by solid (dashed) contours. Here shading is used to show grid boxes with locally significant change (5% level), and this is light gray (medium gray) for areas of wetting (drying). The darker gray shading indicates drying $> -0.8 \text{ mm day}^{-1}$. In (d) gray shading shows the magnitude of warming ($^{\circ}\text{C}$) for all grid boxes that experience significant change (5% level).

a different spatial pattern in each ensemble: covering East Africa and north central Africa in CMIP3 and AO-PPE, and extending to western Africa in CMIP5 and AS-PPE. In northeastern Africa during JAS, there is a strong wet signal in the PPEs, but this is weaker in CMIP5 and largely absent in CMIP3.

The AO-PPE ensemble mean generally shows more precipitation change per degree Celsius of global warming than the CMIP ensembles. This is evident from the rate of change shown in Fig. 5, and is corroborated by projections extracted at 1° , 2° , 3° , and 4°C for AO-PPE (Fig. 1), CMIP3 (JW13), and CMIP5 (not shown). The difference in magnitude is clearest in western Africa, particularly in parts of the Congo basin and western Sahel during JAS: AO-PPE shows an extensive dry signal, of $> 15\% \text{ }^{\circ}\text{C}^{-1}$ in some regions. CMIP3 and CMIP5 also show dry signals, but these are restricted to western Sahel and the southwest Congo basin and are of a much lower magnitude.

These differences in the magnitude of the ensemble mean could be due to greater intermodel agreement in AO-PPE. We might expect more consensus between

perturbed versions of one base model (HadCM3) than for models with different physics, and Fig. 5 indicates that there are more grid points for AO-PPE than the CMIP ensembles for which $> 80\%$ of models agree in the direction of precipitation change (this is particularly noticeable during MAM). AO-PPE models may also be more sensitive to warming, as HadCM3 shows large changes per degree Celsius of ΔT_g relative to other CMIP3 models. The larger response in the ensemble mean is therefore likely to be a combination of greater model consensus and greater sensitivity. A more important issue than the difference in ensemble mean projections is whether any of the individual perturbed model versions show changes outside the range of CMIP3 or CMIP5, and this can be established by examining the range of projections from each ensemble on a regional basis.

2) DIFFERENCES IN THE RANGE OF PROJECTIONS

Area averages of precipitation change relative to control climatologies (%) are shown in Fig. 6 for regions and seasons that have previously been identified as

FIG. 4. Maps of intermodel variance in annual (top) precipitation and (bottom) temperature change associated with $2 \times \text{CO}_2$ for (a),(e) all models in AS-PPE, (b),(f) AS-PPE models with TOA flux imbalance $< 5 \text{ W m}^{-2}$, (c),(g) AS-PPE models with entrainment between 2 and 4, and (d),(h) AS-PPE models with TOA flux imbalance $< 5 \text{ W m}^{-2}$ and entrainment between 2 and 4.

experiencing relatively robust projections in CMIP (East Africa, the Mediterranean, southern Africa, Angola, and west and central Sahel; Christensen et al. 2007; JW13; Christensen et al. 2013) and/or show a contrast between the ensembles in Fig. 5 (Congo basin in DJF and west equatorial Africa in JAS). For each AS-PPE model regional change associated with $2 \times \text{CO}_2$ is plotted against climate sensitivity. For AO-PPE, CMIP3, and CMIP5 the range of modeled changes is shown at specific ΔT_g intervals (1° , 2° , 3°C , etc.), extracted using the methodology described in section 3a. It is not possible to directly compare magnitudes across all four datasets. The figure gives an impression of the level of agreement in the direction of change for all four ensembles, and allows for direct comparison of the amplitude of precipitation responses in AO-PPE, CMIP3, and CMIP5.

In terms of the direction of precipitation change, many signals are shared by the majority of models in all four ensembles. The most consistent responses are the dry signals in the Mediterranean, Angola, and southern Africa. However, some regions show important contrasts

between the datasets with reference to the level of model agreement. In west Sahel, there are several CMIP models that project a large wetting response, most notably the Model for Interdisciplinary Research on Climate (MIROC) Earth system models (ESMs) in CMIP5, but the vast majority of coupled models from the MMEs and from AO-PPE show drying from 2°C of ΔT_g . In contrast the slab models show no agreement on the direction of change. In the Congo basin, the majority of models in CMIP5, AO-PPE, and AS-PPE (subensemble) project wetter conditions, but there is little change in CMIP3.

Differences in the magnitude of change can be measured between AO-PPE, CMIP3, and CMIP5. The ensemble with the largest signals varies regionally. In East Africa during MAM CMIP3 generally shows the largest wetting per degree Celsius of ΔT_g . The median response at 3°C (23%) is much larger than for CMIP5 (4%), and the wettest CMIP3 model, the MIROC, version 3.2 (medium resolution) [MIROC3.2(medres)], has a similar response at 3°C (40%) to the wettest AO-PPE model at 6°C (42%). AO-PPE has more extreme

FIG. 5. Maps of ensemble mean precipitation response. For AS-PPE (subensemble), seasonal mean anomalies associated with $2 \times \text{CO}_2$ (mm day^{-1}) are shown. Locally insignificant (5% level) anomalies are masked in white. For AO-PPE (subensemble), CMIP3, and CMIP5, seasonal mean precipitation anomalies ($\text{mm day}^{-1} \text{ } ^\circ\text{C}^{-1}$) are shown. White indicates $<66\%$ model agreement on direction of change, gray $>66\%$ model agreement or no significance. For all ensembles stippling indicates $>80\%$ model agreement on direction of change.

projections in western Africa, confirming that the stronger ensemble mean response noted in [section 5b\(1\)](#) is the result of greater agreement between models in the direction of change and also larger model projections relative to both CMIP3 and CMIP5. In west equatorial Africa, AO-PPE contains models with drying larger than any in CMIP3 from 3°C, and CMIP5 from 4°C. In Angola, AO-PPE models are also outside the range of CMIP, and in west Sahel the difference is clearest: from 2°C many AO-PPE runs produce dry signals with greater amplitude than any of the CMIP3 or CMIP5 models.

Note that the contrasts among AO-PPE, CMIP3, and CMIP5 might be partly due to natural variability and different scenarios and as opposed to model uncertainty. Comparisons of the same CMIP3 models run in A1B and A2 scenarios do show differences of the same order of magnitude in many regions (see Fig. S1 in the supplemental material); however in western Africa at 2°C and beyond many AO-PPE models are drier than CMIP3 run in both A1B and A2 scenarios, and CMIP5 models run in RCP8.5 scenario, confirming that perturbing the physics of HadCM3 has produced changes outside the range of CMIP.

6. Discussion

Climate change mitigation debates are orientated around degrees of global warming (ΔT_g), and therefore projections presented as a function of ΔT_g have the potential to be useful for decision-makers. Yet, if model results are to support policy, the investigation of uncertainty is paramount. In this paper PPEs have been used to address two uncertainties that are often neglected in regional climate assessments: How would precipitation evolve under higher degrees of global warming? Are there plausible futures that are not represented by the range of models in CMIP? The analysis demonstrates that coupled models produce gradual responses to ΔT_g even at 4°C and beyond, that PPEs provide opportunities for constraining the range of projections, and that there are differences in the range of projections between the CMIP MMEs and MOHC PPEs. Here we discuss the extent to which these findings have connotations for adaptation and mitigation decisions, and the lessons for future climate change assessments, for Africa and beyond.

a. Gradual response to rising global temperatures

AO-PPE models project approximately linear local precipitation change with ΔT_g , suggesting that as global temperature increases, there will be progressive and unidirectional change away from preindustrial conditions. This result has potential implications for policy.

Since larger changes in climate would bring greater challenges for society, the projections could provide evidence to support early mitigation of CO₂ emissions, but also gradual adaptation, as there do not appear to be trend reversals or accelerating rates of change relative to global temperature. For example, the 1.5° and 2°C targets, to be reviewed by the United Nations Framework Convention on Climate Change (UNFCCC) by 2015 ([UNFCCC 2010](#)), show quantitatively but not qualitatively different responses in the AO-PPE projections, and so it is difficult to distinguish between them without impacts assessment. There may be sudden changes in extreme precipitation, nonlinear evaporation responses, or thresholds in systems influenced by mean precipitation change, but there are no dramatic changes in seasonal temperature or precipitation that might support the selection of a particular ΔT_g level as a benchmark for danger. It is possible that our analysis obscures step changes, as have been identified through statistical analysis of observations and model projections for southeastern Australia ([Jones 2012](#)); however, the methodology used here is sufficient to show that there appear to be no trend reversals or large accelerations.

It would be useful to test these results against different scenarios, as [Good et al. \(2012\)](#) find nonlinear precipitation trends in HadCM3 in $4 \times \text{CO}_2$ experiments. We must also interrogate how well HadCM3 and other coupled models are able to simulate the response to rising global temperatures. Many struggle to capture multidecadal variability ([Lau et al. 2006](#)) and the influence of aerosols, which might be associated with trend reversals in regional precipitation, particularly in the Sahel ([Ackerley et al. 2011](#)). It is also unclear whether models can simulate climatic conditions associated with much higher GHGs. GCMs may become less reliable as they are pushed further from today's conditions, just as they often struggle to reproduce paleoclimatic states ([Braconnot et al. 2007](#)). Models of this generation may lack the resolution and complexity to represent nonlinearities in the Earth system, which are more likely to occur as global temperatures are increased ([Lenton et al. 2008](#)). Expert elicitation suggests that there is >56% probability of crossing at least one tipping point if warming exceeds 4°C ([Kriegler et al. 2009](#))—for example, rapid melting of the Greenland Ice Sheet, which could conceivably impact interhemispheric Atlantic sea surface temperature gradients known to influence the West African monsoon (WAM) (e.g., [Folland et al. 1986](#); [Mohino et al. 2011](#)). Yet many studies of twenty-first century changes in the WAM (e.g., [Held et al. 2005](#)) are based on GCMs that, like HadCM3, do not include interactive ice sheets ([Lenton 2011](#)).

FIG. 6. Regional precipitation change (%) associated with $2 \times \text{CO}_2$ in AS-PPE (triangles), and ΔT_g levels for CMIP3, CMIP5, and AO-PPE (subensemble) (purple, blue, and red box plots, respectively: minimum, lower quartile, median, upper quartile, and maximum). For AS-PPE models included in the subensemble are shown as filled triangles, and other models as outlined triangles. Regional coordinates are specified in Table S3 of the supplemental material.

The projections based on AO-PPE therefore provide insufficient evidence on their own to understand the implications of higher degrees of warming for African climate, which remain largely unknown. Regional climate change assessments should acknowledge the uncertainty surrounding pronounced warming and the potential for nonlinear change, as this could affect decisions surrounding mitigation (e.g., when evaluating the

consequences of exceeding 2°C) and adaptation, as it is unclear how strategies based on medium-term scenarios would cope at 4°C and beyond.

b. Ability to constrain a large PPE

The ability to constrain AS-PPE (as described in section 5b) is a key outcome given the widely recognized importance of subselecting models for regional climate

assessments. GCM projections diverge substantially and it is impossible to validate their future simulations, so a range of models must be considered; but it may not be advisable to include all available models, as some are likely to be better than others. Furthermore, regional downscaling and impacts assessment studies are usually restricted in the number of GCM simulations they can incorporate because of computational cost. Selecting models is therefore important for pragmatic as well as scientific reasons, but there is no consistent approach for this in the case of MMEs. Previous attempts to constrain CMIP ensembles have led to contrasting conclusions, for example for the Sahel (Lau et al. 2006; Cook and Vizio 2006). Members of a MME differ from each other in myriad ways, meaning it is not possible to diagnose reasons for differences between them. The models with the best fit to historical observations can be selected, but we cannot determine the reasons for their superior hindcasts and therefore it is difficult to assess whether these models will produce a more reliable response to warming.

In a PPE, the differences between each model version are small and well understood, and therefore the reasons for different modeled responses can be detected, particularly where there are a large number of members. Here, the parameter controlling a strong drying and warming response in the Congo basin in AS-PPE was diagnosed by investigating the association between this response and each of the 31 parameters that is varied within the ensemble. Based on previous research about this parameter, a constraint could then be applied consistently across the ensemble. Such an approach would not have been possible with a MME. The models in CMIP3 and CMIP5 are optimized to fit twentieth-century conditions, meaning there might be less inter-model variability than for AS-PPE, which has been designed to explore parameter space. Nonetheless, the CMIP datasets may still contain implausible models, but these are difficult to identify and remove because the ensembles have not been designed systematically. Large PPEs are easier to constrain, and therefore present greater opportunity to understand the range of plausible futures for African precipitation. Previous studies have used Bayesian statistics to produce probabilistic projections from PPEs (Sexton et al. 2012). While the approach used here is less comprehensive, it demonstrates the potential for simple justifiable constraints.

c. Projections outside the CMIP range

As well as the difficulty in evaluating whether any of the futures projected by an MME are plausible, there is also a high likelihood that there are alternative plausible futures that are not represented. MMEs are not designed

to explore uncertainties in our understanding of physical processes, and therefore in theory they will underestimate uncertainty in responses to global warming. In this study four ensembles are compared to assess whether this is true in practice in the case of African precipitation.

The range of responses is different in each ensemble. CMIP3 and CMIP5, while broadly similar (in agreement with previous research; e.g., Monerie et al. 2012), do show some differences, for example in the Congo basin in DJF, which implies that the range of projections from any one MME might underestimate uncertainty. Comparison with the PPEs supports this conclusion since both project some changes that are not represented by either CMIP3 or CMIP5.

The differences are clearest in west Sahel. Many CMIP models show drying in this region in response to anthropogenic forcing (JW13; Monerie et al. 2012), and the largest projections at 2° (−24%), 3° (−35%), and 4°C (−42%) would likely be dangerous. The Geophysical Fluid Dynamics Laboratory (GFDL) models in CMIP3 show extensive dry signals and have often been perceived to represent a worst case scenario for the Sahel (Held et al. 2005). Here it is shown that some members of CMIP5 show changes of similar magnitude, and that the drying of west Sahel in AO-PPE is even larger: the median response for 3°C is −28% and the three model versions that exceed 6°C (because of large positive feedback mechanisms and the high emissions scenario) all project >40% decreases in precipitation, which is the same amplitude as during with the long-term drought in the 1970s (Held et al. 2005).

The validity of the AO-PPE projections over West Africa deserves further attention given that many coupled models struggle to reproduce the West African monsoon (Roehrig et al. 2013). The standard version of HadCM3 fails to bring the monsoon onto the continent (Cook and Vizio 2006). However, the versions of HadCM3 in AO-PPE do not share this bias (not shown), and it is difficult to explain the large drying in terms of errors in the climatology. Analysis of processes behind the precipitation response would be needed to examine its credibility. Pending further research, the dry signal in AO-PPE constitutes a risk to the Sahel that is not represented in either CMIP3 or CMIP5. Debates about which degree of global warming constitutes dangerous anthropogenic interference for this region might therefore reach different conclusions depending on which ensemble is employed.

The projections from AS-PPE for west Sahel add a further complication: while AO-PPE and CMIP models largely agree that precipitation would decrease (with a few notable exceptions), AS-PPE members are split between wet and dry futures. This undermines the

relative consensus in CMIP and brings into question any adaptation measures for this region which might assume drier conditions: planners would need to prepare for a wider range of possible futures if they were to incorporate uncertainty from all four ensembles. Of course, it may be possible to reduce this range by applying further constraints to the dataset, but without research into mechanisms associated with the modeled responses, it is difficult to assess which projections are more likely.

This paper therefore adds evidence to assertions that adaptation and mitigation decisions should not be based on CMIP3 or CMIP5 alone. The range of projections from any one ensemble should not be viewed as the error bar to measure uncertainty in the climatic response to anthropogenic forcing. There is a wider range of uncertainty, and there is potential for this to be investigated systematically, for example through superensembles with multiple base models run in PPEs.

7. Summary and conclusions

Investigating regional climate changes associated with degrees of global warming (ΔT_g) is important for mitigation and adaptation. However, most existing research has relied on MMEs that do not generate warming $>4^\circ\text{C}$ in the twenty-first century, and that have not been designed to explore modeling uncertainty systematically. In this study two PPEs were employed to address these two issues: to examine the extent to which the implications of global warming for African precipitation deduced from these ensembles might be different from those inferred from either CMIP3 or CMIP5, and to evaluate whether PPEs can provide additional information about uncertainties associated with anthropogenic forcing.

To investigate changes to 4°C and beyond, projections from a coupled PPE (AO-PPE) run in a high emission scenario were presented for 1° – 6°C of ΔT_g . Precipitation anomalies at 2° and 3°C , notably drying in southern Africa during SON and western Africa during JAS, are amplified and extended at 4°C and beyond. This amplification is approximately linear: there is no sign of tipping points being reached. This implies that early mitigation would be beneficial, but it also suggests potential for gradual adaptation. However, the models used may not be capable of representing climatic conditions under such different global mean temperatures, and do not provide potential to explore nonlinearities that are thought to be more likely under high anthropogenic forcing. Therefore further research is needed to test this finding, and the uncertainties associated with higher degrees of warming should be highlighted in regional climate assessments.

AO-PPE and a larger ensemble of 280 atmosphere–slab models (AS-PPE) were also used to test the range of projections for Africa from CMIP3 and CMIP5. First, variability within AS-PPE was explored to eliminate implausible model versions. This revealed that the most dominant signal associated with $2 \times \text{CO}_2$ was the result not of warming but of perturbations: many of the model versions have a negative TOA flux imbalance, creating a land–sea contrast in precipitation fields. These models were removed, alongside ensemble members with implausible entrainment coefficients, here found to be associated with high-amplitude drying and heating of the Congo basin. The application of these constraints was facilitated by the size and systematic nature of the ensemble, suggesting greater potential for model evaluation in PPEs relative to MMEs.

After applying the constraints, there are still differences between the PPEs and the CMIP MMEs. In the western Sahel many members of AS-PPE project wetter futures, undermining the relative consensus on drying in CMIP, while AO-PPE models exhibit large negative anomalies: three ensemble members show more drying at 2°C than the driest projections from CMIP3 (-22%) and CMIP5 (-24%). This finding demonstrates that an MME does not necessarily present a conservative envelope with which to make adaptation and mitigation decisions: the inferred risks of global warming are different depending on which ensemble is employed.

Investigation of African precipitation projections from PPEs therefore suggests that there are deficiencies in the existing climate modeling infrastructure for impact assessment. Regional climate change assessments based only on either CMIP3 or CMIP5 may overlook uncertainties associated with higher degrees of warming and parametric uncertainty. Coupled GCMs do not appear to show tipping points in response to warming, but may lack the complexity to represent the feedbacks involved. MMEs such as CMIP3 and CMIP5 present a range of futures, yet this may contain implausible projections while also excluding other plausible responses. These issues should be emphasized if projections are to be used to inform policy without overconfidence. PPEs provide the opportunity to better understand uncertainties and produce a more defensible range of possible futures.

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