A Framework for Modeling Uncertainty in Regional Climate Change

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A Framework for Modeling Uncertainty in Regional Climate Change

Erwan Monier[*†], Xiang Gao[*], Jeffery Scott[*], Andrei Sokolov[*] and Adam Schlosser[*]

Abstract

In this study, we present a new modeling framework and a large ensemble of climate projections to investigate the uncertainty in regional climate change over the US associated with four dimensions of uncertainty. The sources of uncertainty considered in this framework are the emissions projections (using different climate policies), climate system parameters (represented by different values of climate sensitivity and net aerosol forcing), natural variability (by perturbing initial conditions) and structural uncertainty (using different climate models). The modeling framework revolves around the Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM), an integrated assessment model with an intermediate complexity earth system model (with a two-dimensional zonal-mean atmosphere). Regional climate change over the US is obtained through a two-pronged approach. First, we use the IGSM-CAM framework which links the IGSM to the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM). Secondly, we use a pattern-scaling method that extends the IGSM zonal mean based on climate change patterns from various climate models. Results show that uncertainty in temperature changes are mainly driven by policy choices and the range of climate sensitivity considered. Meanwhile, the four sources of uncertainty contribute more equally to precipitation changes, with natural variability having a large impact in the first part of the 21st century. Overall, the choice of policy is the largest driver of uncertainty in future projections of climate change over the US.

Contents

1. INTRODUCTION

It is well established that the uncertainty in climate system parameters and projected emissions are important drivers of uncertainty in global climate change (Sokolov *et al.*, 2009; Webster *et al.*, 2012). The climate system response to given emissions is essentially controlled by three climate parameters: the climate sensitivity, the strength of aerosol forcing and the ocean heat uptake rate. Future emissions are driven by future economic activity and technological pathways influenced by climate policies and population growth. Other sources of uncertainty in future climate projections, in particular at the regional level, include natural variability and structural uncertainty associated with differences in parameterization in existing climate models. It is well known that year-to-year variability in the climate system is large, in particular at high latitudes, making the emergence of significant climate change slow and signal-to-noise detection difficult (Mahlstein

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et al., 2011; Hawkins and Sutton, 2012; Mahlstein *et al.*, 2012). At the same time, climate projections are heavily influenced by the characteristics of the chosen climate model and global climate models remain inconsistent in capturing regional precipitation changes and other atmospheric processes. Quantifying uncertainty in future regional climate change would prove beneficial to policymakers and impact modeling research groups who investigate climate change and its societal impacts at the regional level, including agriculture productivity, water resources and energy demand (Reilly *et al.*, 2013).

In this study, we introduce a new modeling framework to investigate the uncertainty in regional climate change over the US associated with four sources of uncertainty, namely: (i) uncertainty in the emissions projections, using different climate policies; (ii) uncertainty in the climate system parameters, represented by different values of climate sensitivity and net aerosol forcing; (iii) natural variability, obtained by perturbing initial conditions; and (iv) structural uncertainty using different climate models. The modeling framework is built around the Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM) (Sokolov *et al.*, 2005, 2009), an integrated assessment model with an intermediate complexity earth system model (with a two-dimensional zonal-mean atmosphere). Regional climate change over the US is obtained through a two-pronged approach. First, we use the IGSM-CAM framework which links the IGSM to the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM) Monier *et al.* (2013). Secondly, we use a pattern-scaling method that extends the IGSM zonal mean based on climate change patterns from various climate models (Schlosser *et al.*, 2007).

In this paper, we present a description of the framework for modeling uncertainty in regional climate change. We give a description of the matrix of simulations and present results of regional climate change over the US. We place a particular emphasis on quantifying the range of uncertainty and identifying the contributions of different sources of uncertainty considered in this study. The simulations presented here are part of a multi-model project to achieve consistent evaluation of climate change impacts in the US (Waldhoff *et al.*, 2013).

2. METHODOLOGY

2.1 Modeling Framework

In this study, the core simulations use the MIT IGSM version 2.3 (Dutkiewicz *et al.*, 2005; Sokolov *et al.*, 2005, 2009), an integrated assessment model that couples an earth system model of intermediate complexity to a human activity model. The earth system component of the IGSM includes a two-dimensional zonally averaged statistical dynamical representation of the atmosphere, a three-dimensional dynamical ocean component with a thermodynamic sea-ice model and an ocean carbon cycle (Dutkiewicz *et al.*, 2005, 2009) and a Global Land Systems (GLS) that represents terrestrial water, energy and ecosystem processes (Schlosser *et al.*, 2007), including terrestrial carbon storage and the net flux of carbon dioxide, methane and nitrous oxide from terrestrial ecosystems. The IGSM2.3 also includes an urban air chemistry model (Mayer *et al.*, 2000) and a detailed global scale zonal-mean chemistry model (Wang *et al.*, 1998) that considers the chemical fate of 33 species including greenhouse gases and aerosols. Finally, the human systems component of the IGSM is the MIT Emissions Predictions and Policy Analysis (EPPA) model (Paltsev *et al.*, 2005), which provides projections of world economic development and emissions over 16 global regions along with analysis of proposed emissions control measures.

Since the IGSM includes a human activity model, it is possible to analyze uncertainties in emissions resulting from both uncertainty in model parameters and uncertainty in future climate policy decisions. Another major feature is the flexibility to vary key climate parameters controlling the climate response: climate sensitivity, net aerosol forcing and ocean heat uptake rate. Because the IGSM has a two-dimensional zonal-mean atmosphere, it cannot be directly used to simulate regional climate change. To simulate climate change over the US, we use a two-pronged method.

On the one hand, the MIT IGSM-CAM framework (Monier *et al.*, 2013) links the IGSM to the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM) (Collins *et al.*, 2006b), with new modules developed and implemented in CAM to allow climate parameters to be changed to match those of the IGSM. In particular, the climate sensitivity of CAM is changed using a cloud radiative adjustment method (Sokolov and Monier, 2012). In the IGSM-CAM framework, CAM is driven by greenhouse gas concentrations and aerosol loading computed by the IGSM model as well as IGSM sea surface temperature (SST) anomalies from a control simulation corresponding to pre-industrial forcing superposed on an observed monthly climatology from the merged Hadley-OI SST, a surface boundary dataset designed for uncoupled simulations with CAM (Hurrell *et al.*, 2008). More details on the IGSM-CAM framework can be found in (Monier *et al.*, 2013).

On the other hand, a pattern scaling method (Schlosser *et al.*, 2012) extends the latitudinal projections of the IGSM 2-D zonal-mean atmosphere by applying longitudinally resolved patterns from observations, and from climate-model projections archived from exercises carried out for the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) (Meehl *et al.*, 2007). The pattern scaling method relies on transformation coefficients that essentially reflect the relative value of any given variable at a specific grid cell in relation to its zonal mean. These transformation coefficients are calculated for each month of the year. The following scheme is applied to expand IGSM zonal mean variables across the longitude:

$$V_{x,y}^{IGSM} = \left(C_{x,y}^{OBS} + \frac{dC_{x,y}^{AR4}}{dT_{Global}} \cdot \Delta T_{Global} \right) \cdot V_{y}^{IGSM} \tag{1}$$

$$C_{x,y}^{Obs/AR4} = \frac{V_{x,y}^{Obs/AR4}}{V_{y}^{Obs/AR4}} \tag{2}$$

where x and y are the longitude and latitude of a grid cell, V_{y}^{IGSM} and $V_{x,y}^{IGSM}$ are the original zonal mean IGSM data and the transformed IGSM data, ΔT_{Global} is the global IGSM temperature changes from present day. $C_{x,y}^{OBS}$ are the transformation coefficients for present day and $\frac{dC_{x,y}^{AR4}}{dT_{Global}}$ are the rates of change of the transformation coefficient from IPCC AR4 models with respect to global temperature change. The pattern scaling method is applied to surface air temperature, precipitation, surface wind speed, surface relative humidity, total cloud cover, sea surface temperature and surface water vapor pressure. $C_{x,y}^{OBS}$ are calculated for present-day conditions (for the period 1980–2009) using the Modern Era Retrospective-analysis for Research and Applications (MERRA, Rienecker *et al.*, 2011) for all variables except for precipitation, which relies on the Global Precipitation Climatology Project (GPCP, Adler *et al.*, 2003). GPCP is preferred over MERRA for precipitation because of the presence of substantial biases and discontinuity in the MERRA precipitation over the 1980–2009 period (Kennedy *et al.*, 2011; Rienecker *et al.*, 2011). Finally, $\frac{dC_{x,y}^{AR4}}{dT_{Global}}$ are calculated based on the difference in 10-year mean climatology of $C_{x,y}^{AR4}$ between present-day conditions and the time of doubling of CO_2 in the IPCC simulations with a 1% per year increase in CO_2 (equivalent to year 70 of the simulation), divided by the global mean temperature difference of the same time period. More details on the pattern scaling method can be found in (Schlosser *et al.*, 2012).

The IGSM-CAM simulations provides daily output at a resolution of 2° x 2.5° while the IGSM-pattern scaling method provides monthly output at the same 2° x 2.5° horizontal resolution.

2.2 Description of the Simulations

To investigate the uncertainty in projections of future climate change, a core of 12 simulations with the IGSM are conducted with four values of climate sensitivity and three emissions scenarios are considered. The three emissions scenarios are (i) a reference scenario with unconstrained emissions after 2012 (REF), with a total radiative forcing of 9.7 W/m^2 by 2100; (ii) a stabilization scenario (POL4.5), with a total radiative forcing of 4.5 W/m^2 by 2100; and (iii) a more stringent stabilization scenario (POL3.7), with a total radiative forcing of 3.7 W/m^2 by 2100. The four values of climate sensitivity (CS) considered are 2.0, 3.0, 4.5 and 6°C, which represent respectively the lower bound (CS2.0), best estimate (CS3.0) and upper bound (CS4.5) of climate sensitivity based on the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2007), and a low probability/high risk climate sensitivity (CS6.0). The associated net aerosol forcing was chosen to ensure a good agreement with the observed climate change over the 20th century.

For each set of emissions scenario and climate sensitivity, the IGSM-CAM is run with five different initial conditions (Monier *et al.*, 2013) and the IGSM-pattern scaling is applied to four different patterns of regional climate change. Three IPCC AR4 climate models are chosen along with the IPCC AR4 multi-model ensemble mean. First, the NCAR Community Climate System Model version 3 (CCSM3.0) (Collins *et al.*, 2006a) is chosen to compare with the IGSM-CAM results since both modeling systems have the same atmospheric components. However, because they have different ocean components, simulations with the IGSM-CAM and the IGSM-pattern scaling with CCSM3.0 are not necessarily expected to be identical. Nonetheless, this provides an opportunity to examine if the relative simple pattern-scaling scheme is sufficiently effective to replicate what can be represented in a more sophisticated three-dimensional climate model. The two additional models chosen are the models with the largest and smallest projected increases in precipitation over the US, respectively, the Bjerknes Centre for Climate Research Bergen Climate Model version 2.0 (BBCR_BCM2.0, Otterâ *et al.*, 2009) and the Model for Interdisciplinary Research on Climate version 3.2 medium resolution (MIROC3.2_medres, Hasumi and Emori, 2004). Finally, the multi-model ensemble pattern of regional climate change is obtained from the 17 IPCC AR4 climate models.

Overall, the modeling framework and experimental design used in this study investigates uncertainty in regional climate change associated with four dimensions of uncertainty: emissions projections, the global climate response, the natural variability, and structural uncertainty. A summary of the simulation matrix is shown in **Figure 1** .

3. RESULTS

In the remainder of this article, we refer to present day as the mean over the 1991–2010 period and to 2100 as the mean over the 2091–2110 period.

3.1 Time Series of US Mean Temperature and Precipitation

Figure 2 shows time series of US mean surface air temperature and precipitation anomalies from present day for all the simulations with the IGSM-CAM, their ensemble mean and the IGSM-pattern scaling along with observations. The simulations in this study exhibit a wide range of changes by the end of the century relative to present day. The projected warming ranges from less than 1.0°C to about 10°C while the changes in precipitation range from a decrease of -0.1 mm/day to increases up to 0.7 mm/day. The largest changes generally occur for the reference

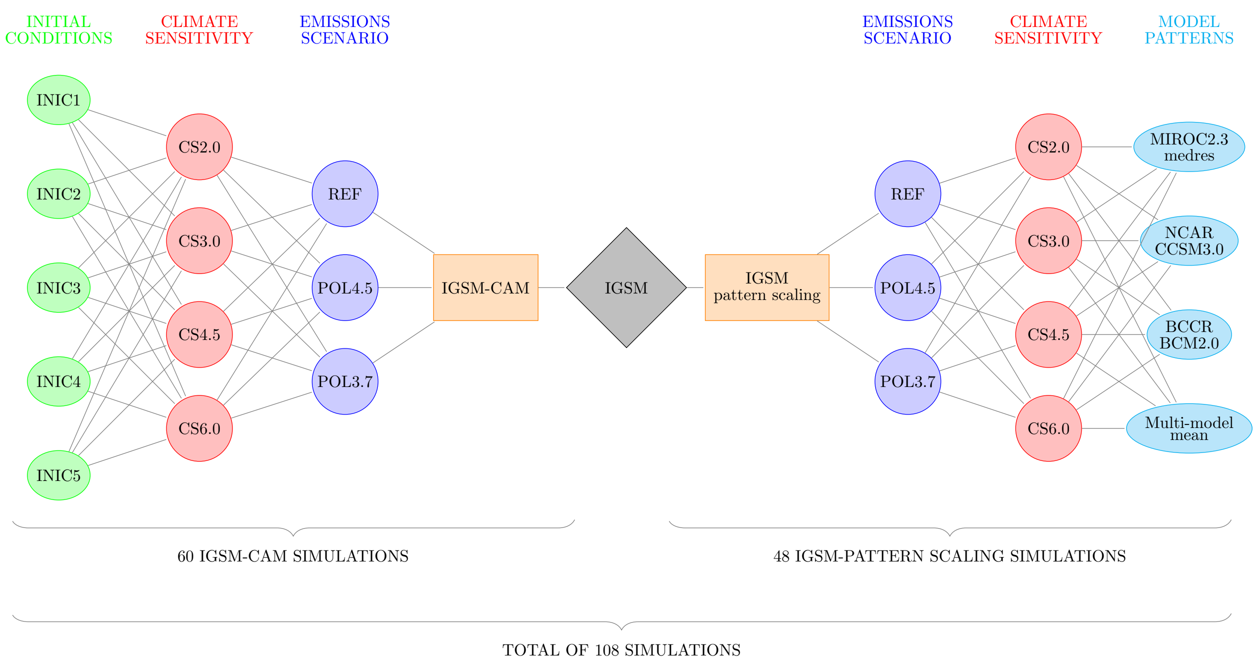

Figure 1. Summary of the experimental design of the modeling framework and the simulation matrix used in this study.

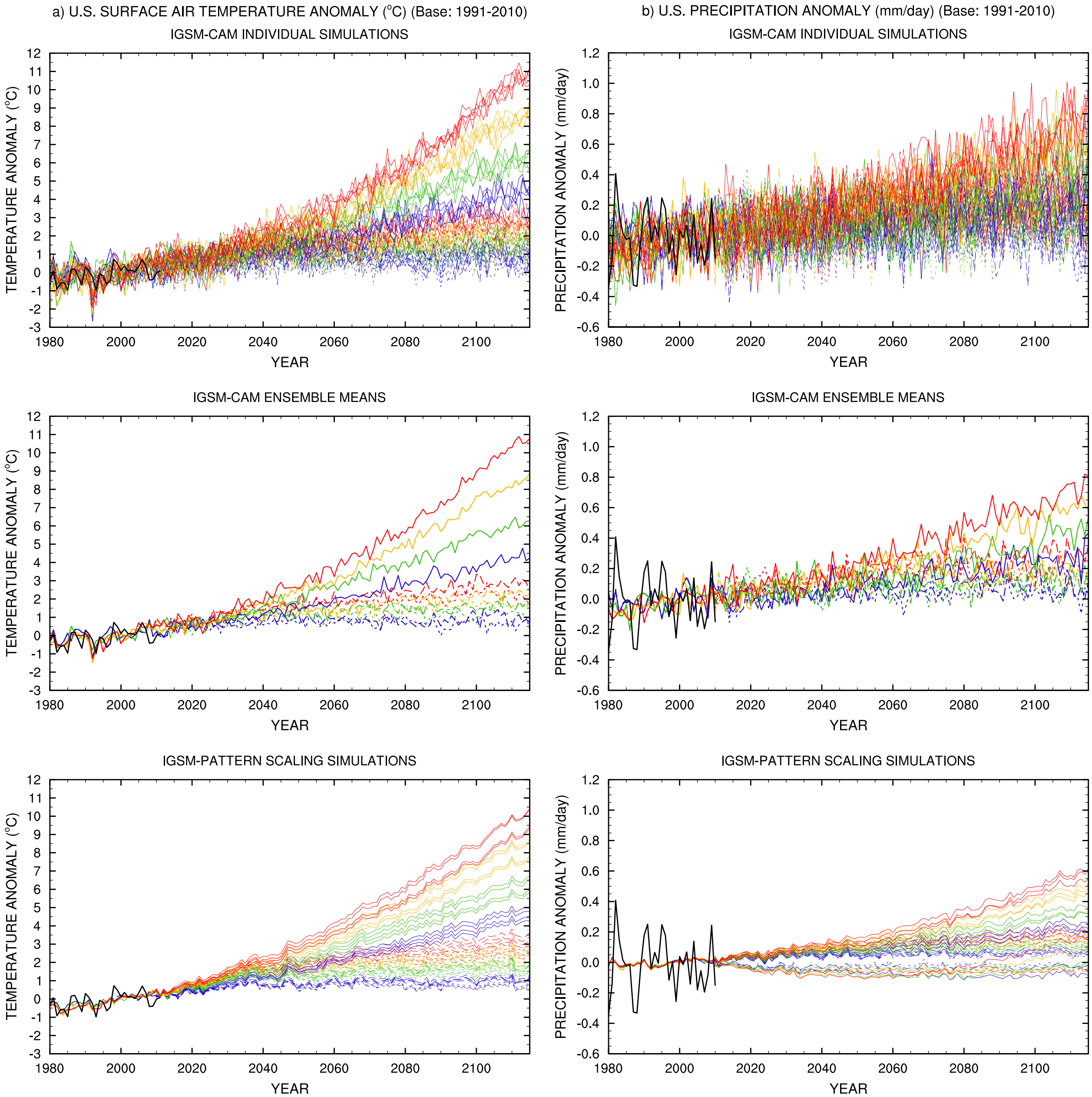

Figure 2. Time series of US mean a) surface air temperature and b) precipitation anomalies from present day (1991–2010 mean) for all the simulations with the IGSM-CAM, their ensemble mean and the IGSM-pattern scaling along with observations. The black lines represent observations, the Goddard Institute for Space Studies (GISS) surface temperature (GISTEMP, Hansen *et al.*, 2010) and the 20th Century Reanalysis V2 precipitation (Compo *et al.*, 2011). The blue, green, orange and red lines represent, respectively, the simulations with a climate sensitivity of 2.0, 3.0, 4.5 and 6.0°C. The solid, dashed and dotted lines represent, respectively, the simulations with the reference scenario, stabilization scenario at 4.5 W/m^2 and the stabilization scenario at 3.7 W/m^2.

emissions scenarios and for the highest climate sensitivity. The IGSM-CAM simulations display a strong interannual variability, especially for precipitation, which is in very good agreement with the observations over the historical period. As a result, comparing two particular simulations to identify the impact of, for example, the implementation of a stabilization policy or different values of climate sensitivity, is generally difficult. However, once the five-member ensemble is averaged, the signal is more easily extracted from the noise. Meanwhile, simulations with the IGSM-pattern scaling method show limited interannual variability, even less than the IGSM-CAM ensemble mean simulations. This is because the temporal variability in temperature and precipitation in the IGSM-pattern scaling method is controlled entirely by the IGSM zonal mean, which displays a much weaker variability than would any particular grid cell along the same latitude. For this reason, the IGSM-pattern scaling method underestimates natural variability and its potential changes, as well as climate and weather extreme events. Finally, the choice of the model for the pattern scaling method has limited impact on the US mean surface air temperature changes but a wide range of changes in projected precipitation changes. One model in particular is showing decreases in the US mean precipitation, except for the CS4.5_REF and CS6.0_REF after 2080. This reflects the large uncertainty in projections of precipitation, in particular over the US, by the IPCC AR4 models (Randall *et al.*, 2007) and the strength of the IGSM-pattern scaling method in accounting for structural uncertainty.

3.2 Regional Patterns of Change

Figure 3 shows maps of changes in surface air temperature in 2100 relative to present day for the IGSM-CAM and IGSM-pattern scaling simulations, for different initial conditions, different values of climate sensitivity, different emissions scenarios and different models. Overall, Figure 3 displays a wide range of warming amongst the simulations presented in this study. The IGSM-CAM simulations with different initial conditions under the same CS3.0_REF scenario show very similar patterns of temperature change. The largest warming takes place over the Great Basin while the West South Central States show the least amount of warming. Differences between the five initial conditions are less than 1.0°C, largely due to the use of 20-year averages in this analysis. The IGSM-CAM ensemble mean for the REF emissions scenario with different values of climate sensitivity show a wide range in the magnitude of the warming. The largest warming is seen for the ensemble mean with the highest climate sensitivity, where increases in temperature over the Great Basin reach up to 12.0°C. On the other hand, the warming is reduced to just 5°C in the ensemble mean with the lowest value of climate sensitivity. The differences in warming due to the implementation of different emissions scenarios under the same climate sensitivity (CS3.0) can also be seen in Figure 3. It shows that both stabilization policies greatly reduce the warming, with increases in temperature less than 3.0°C over the entire US. Finally, simulations with the IGSM-pattern scaling method for the same CS3.0_REF scenario show that different models display different patterns of warming. In particular, the location of the largest warming differs significantly between the models. Furthermore, the maximum warming amongst the four pattern-scaling models and the IGSM-CAM for the same REF_CS3.0 scenario ranges from 6.0 to 8.0°C.

A similar analysis for changes in precipitation is shown in **Figure 4**. The IGSM-CAM generally shows decreases in precipitation on the West Coast and increases everywhere else. The

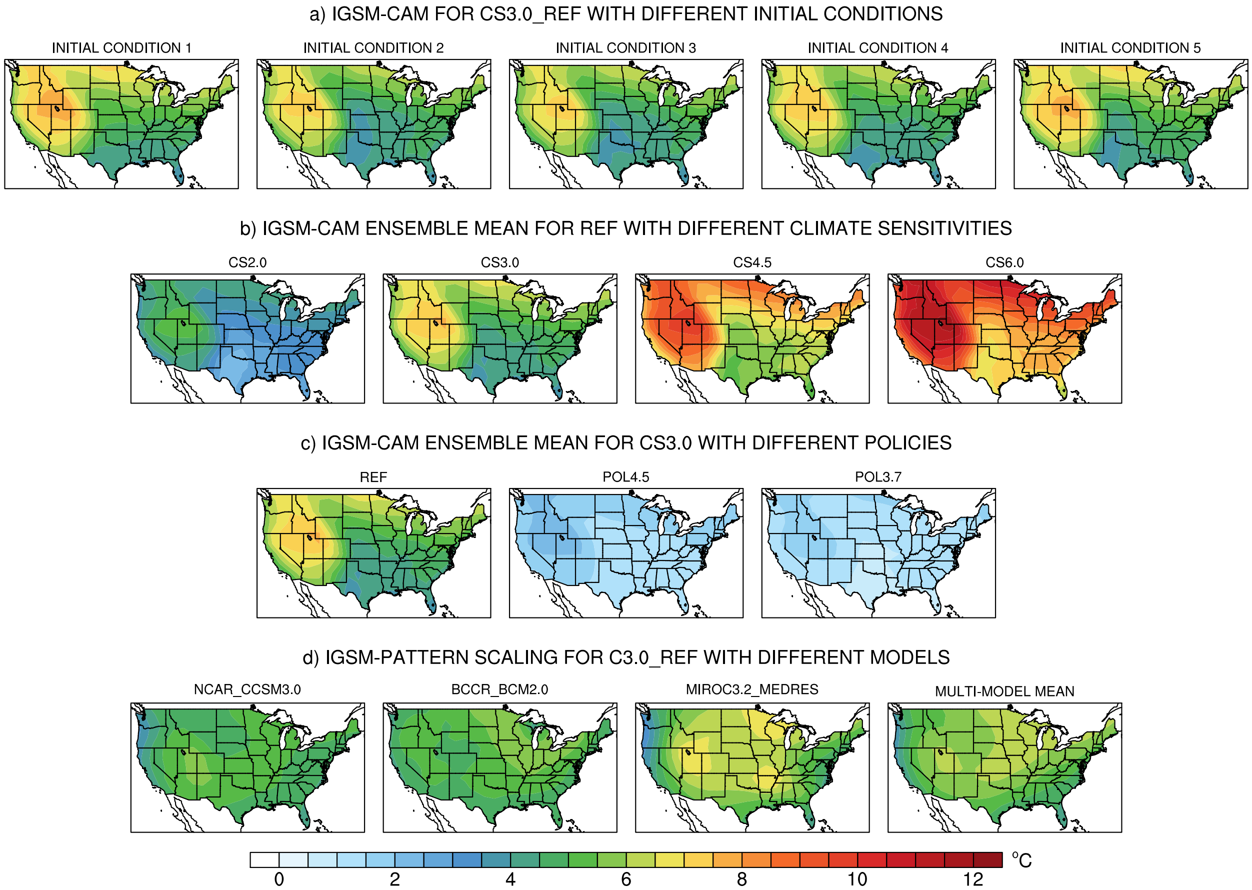

Figure 3. Changes in surface air temperature (in °C) in 2100 (2091–2110 mean) relative to present day (1991–2010 mean) for a) the IGSM-CAM simulations with different initial conditions under the REF_CS3.0 scenario, b) the IGSM-CAM ensemble mean with different climate sensitivities under the REF scenario, c) the IGSM-CAM ensemble mean with different emissions scenarios under the CS3.0 scenario and d) the IGSM-pattern scaling with different climate models under the REF_CS3.0 scenario.

use of different initial conditions lead to distinctively different locations and magnitudes of maximum changes in precipitation as well as a zero-change line in a slightly different location. For example, the simulation with initial condition 5 displays the largest decrease in precipitation, located on the coast of Oregon, reaching up to 1 mm/day compared to around 0.5 mm/day in the other simulations. The magnitude of the precipitation decrease over the West Coast can be larger between IGSM-CAM simulations with different initial conditions but under the same CS3.0_REF scenario than between ensemble simulations with different values of climate sensitivity under the same REF scenario. This underlines the fact that initial conditions have a larger impact on regional precipitation changes than on temperature. The impact of the climate sensitivity appears to be strongly localized. The greater the climate sensitivity, the larger the increase in precipitation over the Great Plains. On the other hand, the implementation of a stabilization policy lead to decreases in the magnitude of precipitation changes over the entire US. Finally, Figure 4 shows the difference in the patterns of precipitation changes for the IGSM-pattern scaling. CCSM3.0 simulates decreases in precipitation over California, Arizona, most of New Mexico and the

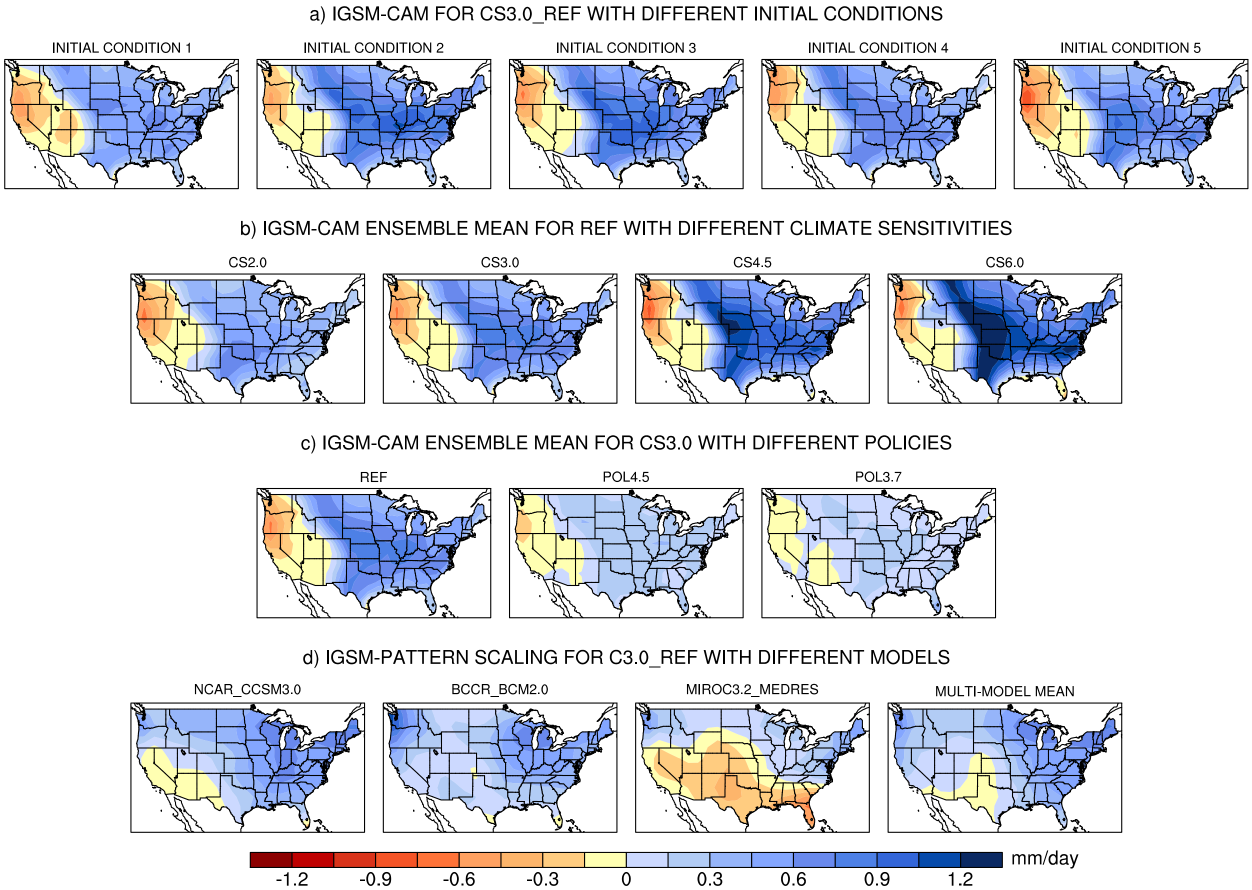

Figure 4. Changes in precipitation (in mm/day) in 2100 (2091–2110 mean) relative to present day (1991–2010 mean) for a) the IGSM-CAM simulations with different initial conditions under the REF_CS3.0 scenario, b) the IGSM-CAM ensemble mean with different climate sensitivities under the REF scenario, c) the IGSM-CAM ensemble mean with different emissions scenarios under the CS3.0 scenario and d) the IGSM-pattern scaling with different climate models under the REF_CS3.0 scenario.

western part of Nevada, and increases everywhere else. This pattern bears some resemblance with the pattern of precipitation of the IGSM-CAM, except that the latter extends more along the north of the Pacific Coast. BCCR_BCM2.0 displays increases in precipitation over the entire US, except for the southernmost part of Texas and Florida. MIROC3.2_MEDRES presents drying over the Southern and Southwestern US and moistening elsewhere. Finally, the multi-model mean display decreases in precipitation over the Western Texas, most of New Mexico and parts of Colorado, Kansas and Arizona.

Figure 5 shows maps of the mean spread of temperature and precipitation changes in 2100 relative to present day for each source of uncertainty considered in this study (policy, climate sensitivity, initial condition and model). The mean spread is defined as the standard deviation across a source of uncertainty averaged over the other sources of uncertainty. Figure 5 reveals that for temperature changes the mean spread displays little spatial heterogeneity. The largest source of uncertainty is the choice of policy, with a mean spread between 2.0 and 3.0°C over most of the US. The spread from the climate sensitivity is also substantial, with values between 1.0 and

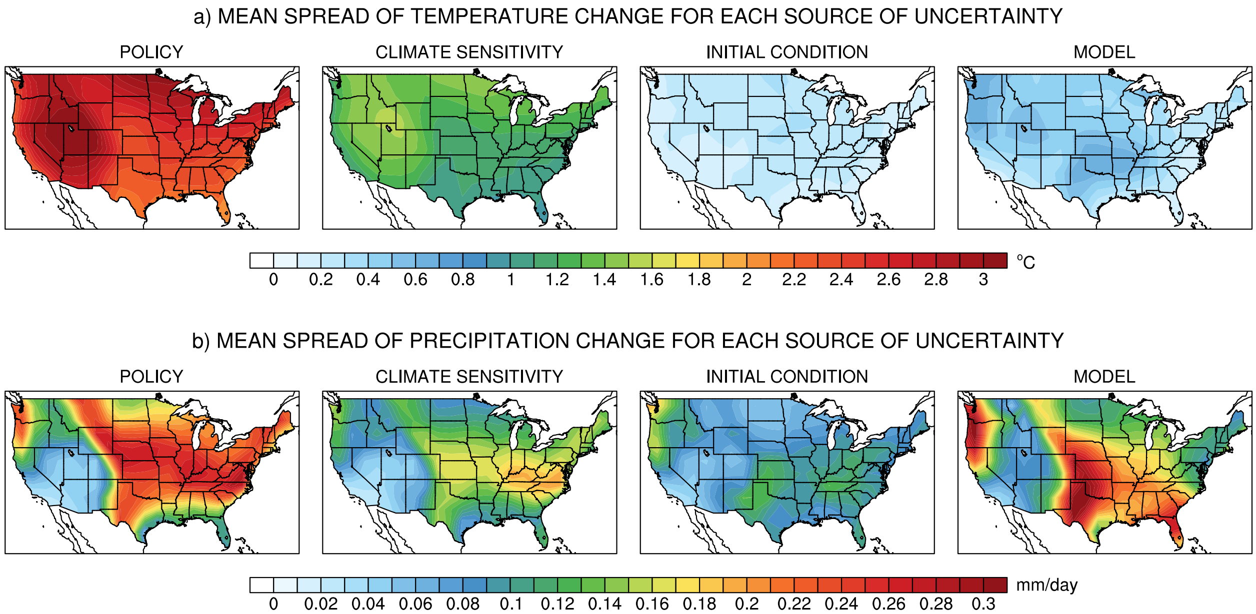

Figure 5. Maps of the spread of changes in a) temperature (in °C) and b) precipitation (in mm/day) in 2100 (2091–2110 mean) relative to present day (1991–2010 mean) for each source of uncertainty (policy, climate sensitivity, initial condition and model pattern). The spread is defined as the standard deviation across a source of uncertainty averaged over the other sources of uncertainty.

1.7°C. The impact of the choice of the model on temperature changes is much smaller, with a mean spread reaching 0.8°C in only a few areas. Finally, the spread from initial conditions is small, less than 0.5°C over the entire US. For precipitation changes, the spread of each source of uncertainty is more heterogeneous. A particular feature is the small spread per the Southwest region covering Southern California, Arizona, Utah and southern Nevada in all sources of uncertainty, indicating that this region shows the least amount of uncertainty in precipitation changes. The choice of policy and of model are the largest contributors of uncertainty in precipitation changes, with a mean spread larger than 0.2 mm/day in large parts the Unites States. Meanwhile, the mean spread associated with climate sensitivity lies between 0.08 and 0.18 mm/day tousled of the Southwestern US. The impact of initial conditions appears limited in most regions except over the northern Pacific Coast, where the mean spread is larger than for the climate sensitivity, and in the Southern US.

Finally, **Figure 6** shows the same analysis as done for Figure 5 based on the US mean surface air temperature and precipitation changes in 2025 (2016–2035 mean), 2050 (2041–2060 mean), 2075 (2066–2080 mean) and 2100 (2091–2110) mean relative to present day (1991–2010 mean). It reveals that the relative contribution from each source of uncertainty changes over time and that uncertainty sources contribute differently to temperature and precipitation changes. For changes in temperature, the initial conditions are the largest source of uncertainty in 2025 but the spread from initial conditions remains constant in time. As a result, its relative contribution decreases in time. By 2050, the impact of policy and climate sensitivity are larger than that of the initial conditions and their relative contribution continues to increase as the century advances. By 2100,

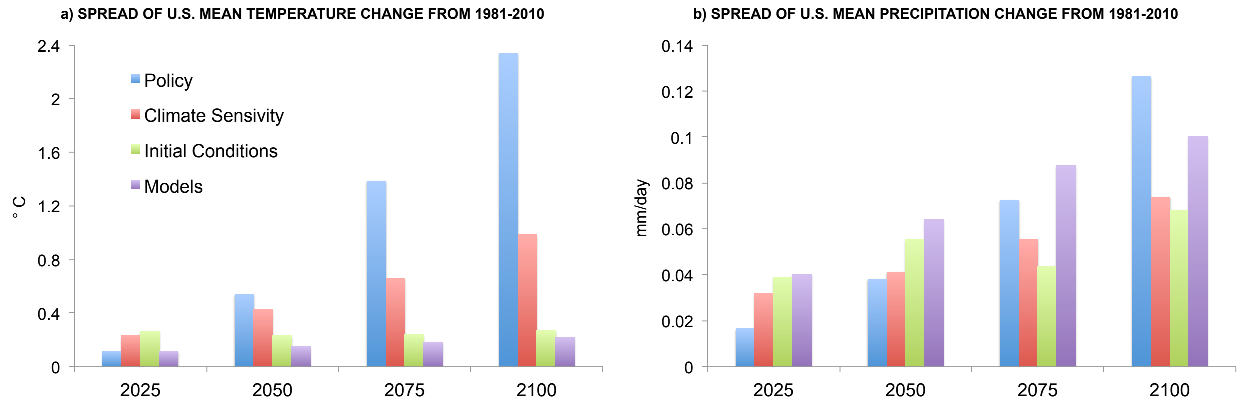

Figure 6. Spread of changes in a) US mean temperature (in °C) and b) US mean precipitation (in mm/day) in 2025 (2016–2035 mean), 2050 (2041–2060 mean), 2075 (2066–2085 mean) and 2100 (2091–2110 mean) relative to present day (1991–2010 mean) for each source of uncertainty (policy, climate sensitivity, initial condition and model pattern). The spread is defined as the standard deviation across a source of uncertainty averaged over the other sources of uncertainty.

the spread in temperature changes caused by differences in policy is more than twice as large as the spread associated with the climate sensitivity. Meanwhile, the spread of temperature changes associated with the choice of model is the smallest spread for every period analyzed. The impact of the different sources of uncertainty on changes in precipitation is quite different from the impact on temperature changes. In particular, the structural uncertainty associated with different models is the largest source of uncertainty until 2100, when it is surpassed by policy. In addition, the contribution of the initial conditions is on par with the contribution of the climate sensitivity. The initial conditions are until 2075. Figure 6 underlines the complexity of the uncertainty in projections of both regional surface temperature and precipitation. It also demonstrates the importance of considering multiple sources of uncertainty in future regional climate projections.

4. SUMMARY AND CONCLUSION

As part of a multi-model project to achieve consistent evaluation of climate change impacts in the US (Waldhoff *et al.*, 2013), we use a series of 12 core simulations with the MIT IGSM with three different emissions scenarios and four values of climate sensitivity (Paltsev *et al.*, 2013). We obtain regional climate change over the US using a two-pronged approach. On the one hand, we use the MIT IGSM-CAM framework, which links the IGSM to the CAM model. On the other hand, we apply a pattern scaling method to extend the latitudinal projections of the IGSM 2-D zonal-mean atmosphere by applying longitudinally resolved patterns from IPCC AR4 climate models. The IGSM-CAM is run for each of the 12 core simulations with five different initial conditions to account for uncertainty in natural variability. The IGSM-pattern scaling method is applied to three IPCC AR4 models and the multi-model mean based on 17 IPCC AR4 models. The three models chosen are the NCAR CCSM3.0, which shares the same atmospheric model as the IGSM-CAM; BCCR BCM2.0, which projects the largest increases in precipitation over the

US; and MIROC3.2 medres, which predicts the least amount of precipitation increases over the US. This new framework for modeling uncertainty in regional climate change covers four dimensions of uncertainty: projected emissions (different climate policies); global climate response (different values of climate sensitivity and net aerosol forcing); natural variability (different initial conditions); and structural uncertainty (different climate models). Altogether, these simulations provide an efficient matrix of future climate projections to study climate impacts under uncertainty.

The simulations display a large range of US mean temperature and precipitation changes, and different regional patterns of change. In addition, the two different methods have very different treatments of interannual variability. The IGSM-CAM physically simulates changes in both mean climate and extreme events (Monier and Gao, 2013), but relies on one particular model. The pattern scaling approach allows the spatial patterns of regional climate change of different climate models to be considered, but significantly underestimates year-to-year variability and cannot simulate extreme events or their potential changes under climate change. Together, these two methods provide complementary skills and an efficient framework to investigate uncertainty in future projections of regional climate change. The limitations of each methodology should be carefully accounted for when using this framework to drive impact models. In particular, researchers using climate simulations to drive impact models should always use individual model simulations and not ensemble mean simulations in order to account for natural variability. That is because natural variability is a driver for extreme climate and weather events, which can dominate impacts, and would not be accounted for in ensemble mean simulations.

Finally, an analysis of the contribution of the four different sources of uncertainty reveals that choice of policy and value of the climate sensitivity have the largest impact on surface air temperature changes (choice of policy being the dominant contributor), while the contributions from natural variability and structural uncertainty are small. On the other hand, the contributions of the four sources of uncertainty are more equal for changes in US mean precipitation but show large spatial heterogeneity. The impact of the initial conditions on precipitation changes is substantial, in particular until 2050, on par with the impact of the climate sensitivity. The structural uncertainty is the largest source of uncertainty until 2075. After that, the choice of policy dominates. In light of these new results, it appears clear that the largest source of uncertainty in future projections of climate change over the US is also the only source that society has a control over: the emissions scenario. This should reflect the need to seriously consider implementing a global climate policy aimed at stabilizing greenhouse gases concentrations in the atmosphere.

It should be noted that the contribution of each source of uncertainty depends strongly on the particular samples and choices made in this study. The implementation of only moderate policies or the choice of only low values of climate sensitivity would certainly decrease the estimates of their contribution to the overall changes. Nonetheless, this analysis demonstrates the relevance of modeling each source of uncertainty. It further demonstrates the need of new and more complete frameworks for modeling uncertainty in regional climate change.

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