MIT JOINT PROGRAM
SCIENCE POLICY
GLOBAL CHANGE

Report 320
September 2017

Probabilistic projections of the future climate for the world and the continental USA

Andrei Sokolov, Xiang Gao, Sergey Paltsev, Erwan Monier, Henry Chen, David Kicklighter, Ronald Prinn, John Reilly and Adam Schlosser

MIT Joint Program on the Science and Policy of Global Change combines cutting-edge scientific research with independent policy analysis to provide a solid foundation for the public and private decisions needed to mitigate and adapt to unavoidable global environmental changes. Being data-driven, the Joint Program uses extensive Earth system and economic data and models to produce quantitative analysis and predictions of the risks of climate change and the challenges of limiting human influence on the environment—essential knowledge for the international dialogue toward a global response to climate change.

To this end, the Joint Program brings together an interdisciplinary group from two established MIT research centers: the **Center for Global Change Science (CGCS)** and the **Center for Energy and Environmental Policy Research (CEEPR)**. These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the program's work lies MIT's Integrated Global System Model. Through this integrated model, the program seeks to discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This reprint is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—Ronald G. Prinn and John M. Reilly,
Joint Program Co-Directors

MIT Joint Program on the Science and Policy of Global Change

Massachusetts Institute of Technology
77 Massachusetts Ave., E19-411
Cambridge MA 02139-4307 (USA)

T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/

Probabilistic projections of the future climate for the world and the continental USA

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Abstract: In this paper, we study possible impacts of anthropogenic greenhouse gas (GHG) emissions on the 21st century climate on the continental USA using the MIT Integrated Global System Model (IGSM) framework. Climate change simulations use an emissions scenario developed with the IGSM's Economic Projection and Policy Analysis (EPPA) Model. The scenario represents a global emission path consistent with the current view on the trajectories of technological and economic development. The estimates of possible changes in climate are based on an ensemble of 400 simulations with the IGSM's MIT Earth System Model (MESM), a model of intermediate complexity. Regional changes over the USA were obtained using statistical downscaling that incorporates results from the simulations with the CMIP5 Atmosphere-Ocean General Circulation Models (AOGCMs). The results show that under the considered emissions scenario, surface air temperature averaged over the continental USA increases by 2.6 to 4.4K by the last decade of the 21st century (90% probability interval) relative to pre-industrial temperatures, compare to 2.3 to 3.4K for the whole globe. Corresponding changes in precipitation are -0.65 to 0.34 mm/day and 0.13 to 0.22 mm/day, respectively. There is significant variation in the geographical distribution of those changes among the ensemble simulations.

1. Introduction

Uncertainties in projections of future climate are associated with uncertainties in the growth of the world economy and the resulting uncertainties in anthropogenic emissions of greenhouse gases as well as with uncertainties in climate system response to those emissions. The MIT IGSM framework was developed to study possible changes in global and regional climate in a probabilistic manner. Two major components of this framework are the MIT Economic Projection and Policy Analysis (EPPA, Paltsev *et al.*, 2005; Chen *et al.*, 2016) model and the MIT Earth System Model (MESM, Sokolov *et al.*, 2005 and 2017). A number of probabilistic studies on the future climate were carried out with previous versions of EPPA and MESM (e.g. Sokolov *et al.*, 2009; Webster *et al.*, 2003 and 2012). However, our understanding of the underlying economic processes represented in the EPPA model and our knowledge about past climate that is used to calibrate MESM has continued to change, making it useful to update estimates of both economic and climate uncertainties.

For example, estimates of probability distributions for climate parameters defining climate system response to external forcing strongly depend on the length of observational records used to determine these distributions (e.g. Libardoni, 2017). In addition, estimates for the past natural and anthropogenic forcings are regularly updated which also affects climate parameter estimates (e.g. Forest *et al.*, 2006 and 2008; Libardoni, 2017). Projections of the future economic development of different regions also change (Webster *et al.*, 2008; Reilly *et al.*, 2015).

In this paper, we focus on uncertainty in future climate associated with an uncertainty in earth system processes using our latest estimates of climate model parameters (Libardoni, 2017; Sokolov *et al.*, 2017) and a single emission scenario (Reilly *et al.*, 2015). In addition to the global estimates we also show projections for the continental USA obtained using a statistical downscaling approach described by Schlosser *et al.* (2013).

2. Model Description and Simulation Setup

The MIT Economic Projection and Policy Analysis (EPPA) model provides a multi-sector representation of the global economy (Paltsev *et al.*, 2005; Chen *et al.*, 2016). The EPPA model projects economic variables (GDP, consumption, sectoral output, trade etc.), energy flows (power generation mix, primary energy mix, international energy trade, etc.), and emissions of GHGs from combustion of carbon-based fuels, industrial processes, waste handling and agricultural activities through 2100. The model includes representation of CO_2 and non-CO_2 (CH_4, N_2O, HFCs, PFCs and SF_6) greenhouse gas emissions abatement, and calculates reductions from gas-specific control measures as well as those occurring as a byproduct of actions directed at CO_2. The model also tracks several major air pollutants: sulfates (SO_x), nitrogen oxides (NO_x), black carbon (BC), organic carbon (OC), carbon monoxide (CO), ammonia (NH_3), and non-methane volatile organic compounds (VOCs).

The EPPA model explicitly represents interactions both among sectors, through inter-industry inputs, and among regions, via bilateral trade flows. The model simulates economy-wide production in each region at the sectoral level. Sectoral output is produced from primary factors including multiple categories of depletable and renewable natural capital, produced capital, and labor. Intermediate inputs to sectoral production are represented through a complete input-output structure. The economic scenario used in this study is described in Reilly *et al.* (2015).

The MIT Earth System Model (MESM) is an earth system model of intermediate complexity that couples sub-models of all main components of the climate system. It includes a zonally averaged atmospheric model with fully interactive chemistry, a land model, a terrestrial ecosystem model and a simplified ocean model with a carbon cycle. As a result, MESM is able to simulate the main interactions among these different components of the earth system. Values of model parameters defining climate sensitivity, rate of oceanic heat uptake and strength of the carbon cycle can be varied. A detailed description of the current version of MESM is given in Sokolov *et al.* (2017), together with the results that show its behavior in historical climate simulations.

To estimate the uncertainty in future climate, we carried out an ensemble of climate simulations using 400 samples from the probability distributions of climate parameters described in Libardoni (2017). Climate simulations with MESM are carried out in two stages: historical simulations from 1861 to 2005 and forward climate simulations from 2006 to 2100. During the first stage, MESM is run in a concentration-driven mode forced by observed changes in natural and anthropogenic forcing. In the second stage, MESM is run in an emissions-driven mode and forced by anthropogenic greenhouse gases emissions produced by the EPPA model.

Sokolov *et al.* (2017) compared the MESM performance with the results of the CMIP5 multi-model ensemble, using 400 simulations with 1% per year increase in CO_2 concentration. **Table 1** shows 90% probability ranges for climate sensitivity, transient climate response (TCR) and the transient climate response to cumulative carbon emissions (TCRE).

Ranges of the different climate characteristics obtained in the ensemble of simulations with MESM agree well with the ranges obtained from the simulations with the CMIP5 models.[1]

3. Results and Discussion

In the Business As Usual (BAU) emissions scenario used in this study, CO_2 emissions initially decrease slightly from about 9.6 GtC/y in 2015 to about 9.3 GtC/y in 2030, reflecting recent energy policy commitments of many countries (**Figure 1**). After 2030 they start to increase again, reaching 11.5 GtC/y in 2100 (19% increase relative to 2015). Equivalent CO_2 emissions, after a small drop between 2015 and 2020, rise from 13.9 GtC-eq/y in 2015 to 18.6 GtC-eq/y in 2100 (33% increase), with a strong increase in methane emissions (by 75%) over this period contributing to the overall trend. A detailed description of the drivers for this scenario is given by Reilly *et al.* (2015). In spite of the initial decrease in CO_2 emissions, concentrations are rising continually throughout the century (**Figure 2**). By the last decade of the 21st century, simulated CO_2 concentrations are 605–680 ppm (90% interval) with a median value of about 650 ppm. Since the anthropogenic emissions scenario is unchanged, these differences in CO_2 concentrations among ensemble members are explained by differences in the carbon uptake by the land and ocean (**Figure 3**) associated with uncertainty in the strength of the carbon cycle. Those un-

1 See Sokolov *et al.* (2017) for more detailed comparison.

Table 1. Mean values and 5–95% probability intervals for climate sensitivity, TCR and TCRE from the MESM ensemble and CMIP5 multi-model ensemble. Data for CMIP5 climate sensitivity and TCR are from IPCC (2013) and for TCRE from Gillett *et al.* (2013).

	Climate sensitivity *K*	**TCR** *K*	**TCRE** *K/ EgC*
MESM	3.2 (2.4–4.6)	1.7 (1.4–2.0)	1.6 (1.2–1.9)
CMIP5	3.2 (1.9–4.5)	1.8 (1.2–2.4)	1.4 (0.7–2.0)

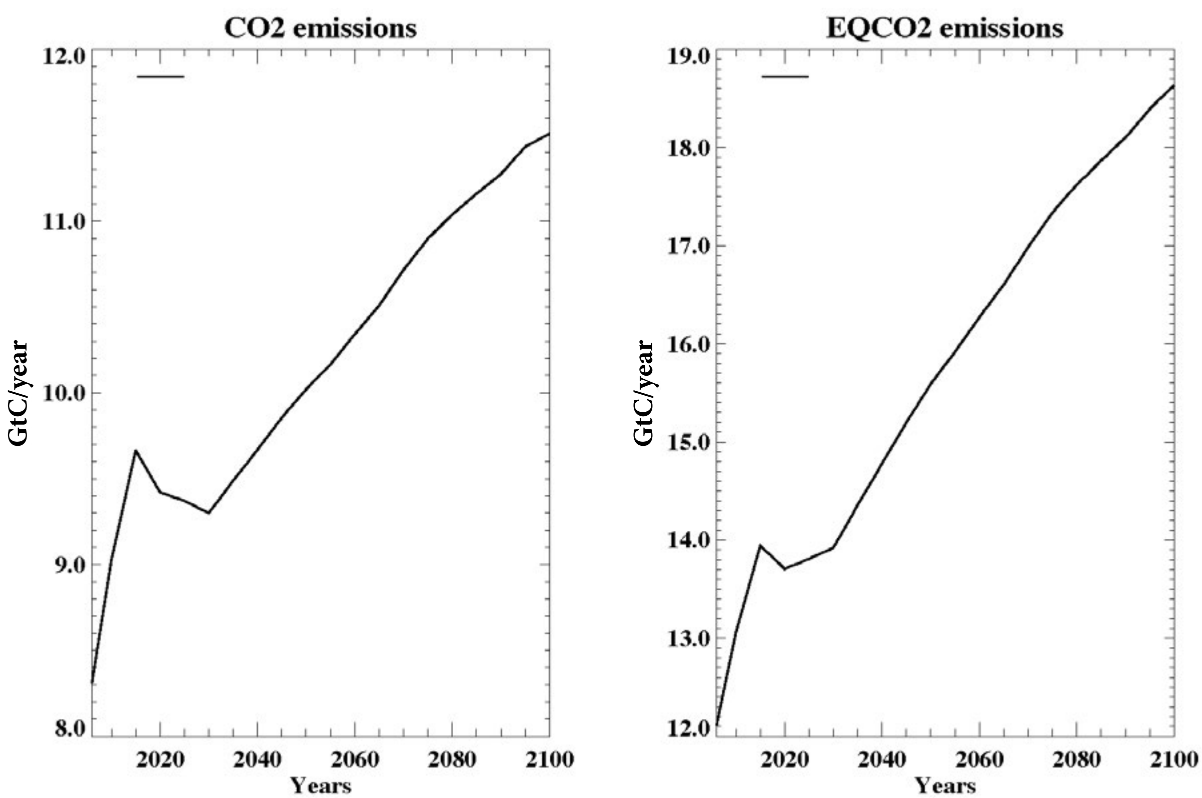

Figure 1. CO_2 and equivalent CO_2 emissions.

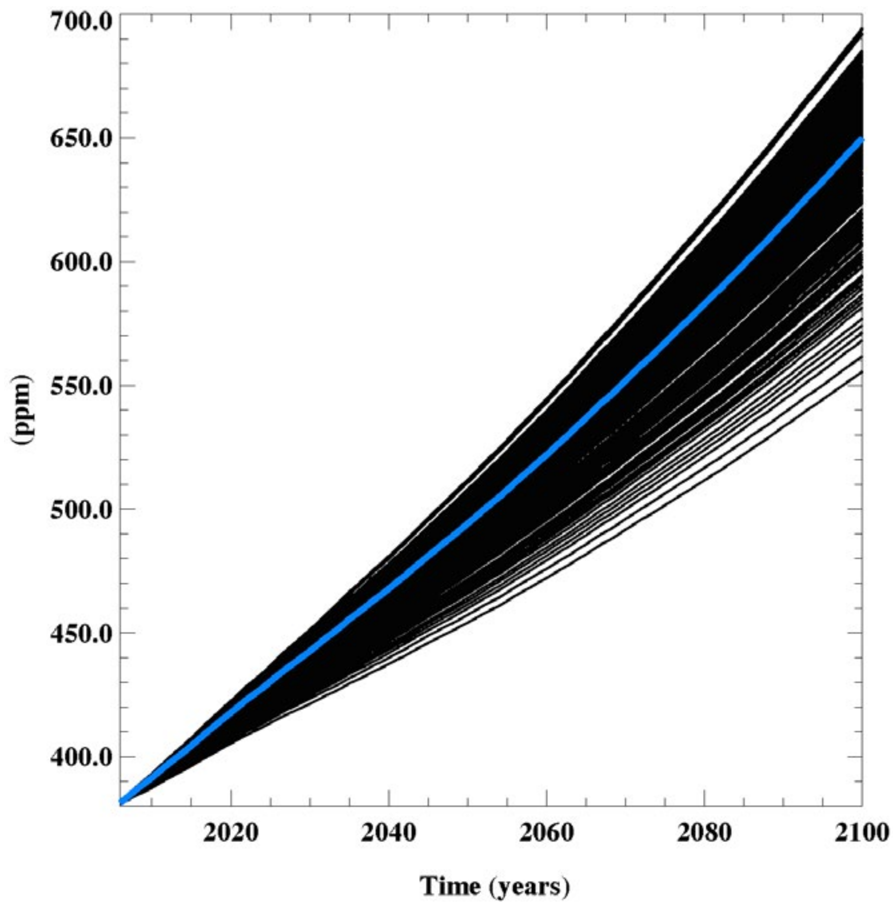

Figure 2. CO_2 concentrations.

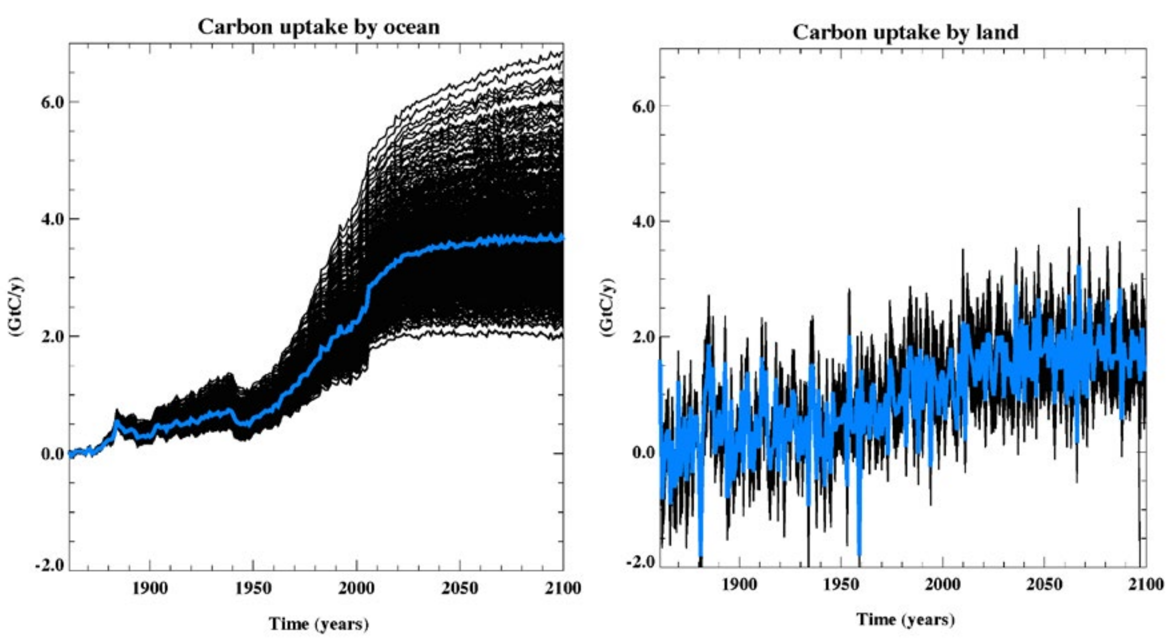

Figure 3. Carbon uptake by ocean (left) and terrestrial ecosystem (right).

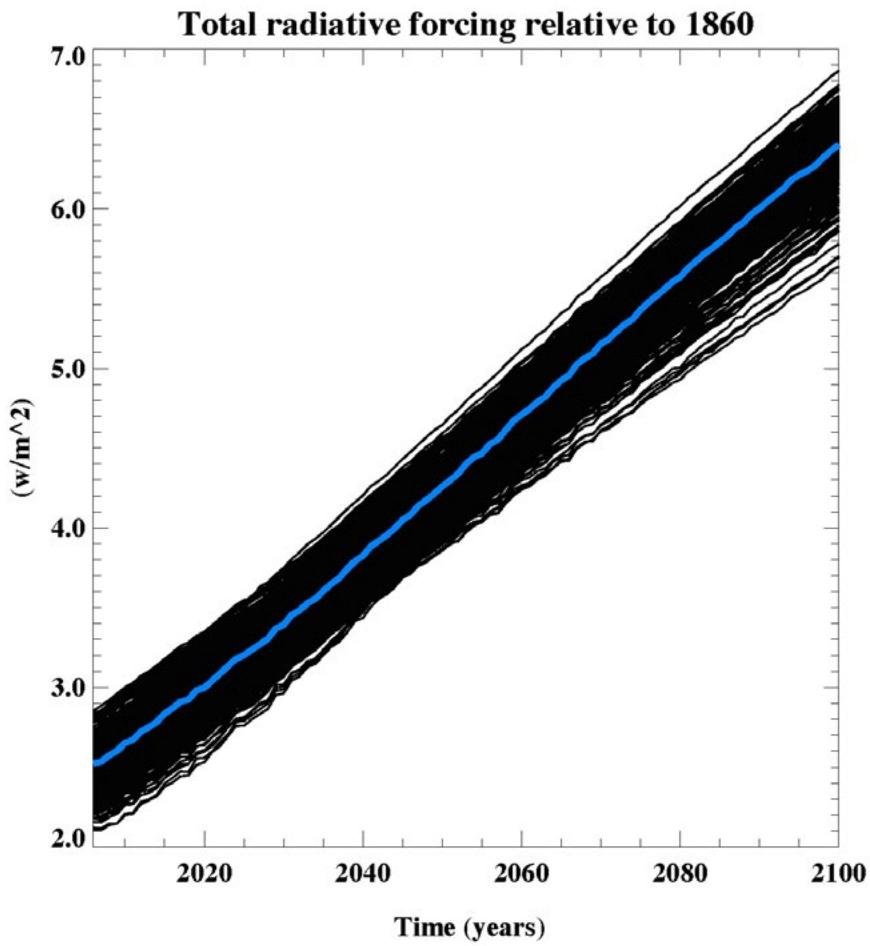

Figure 4. Total radiative forcing relative to 1860.

certainties are taken into account by using different values of the carbon mixing rates into the deep ocean and the of rates CO_2 fertilization in terrestrial ecosystems.[2] Carbon uptake by both the ocean and terrestrial ecosystems increase until around 2040 and then start to decline. Such behavior is consistent with the results produced by most of the CMIP5 earth system models (Friedlingstein *et al.*, 2014). Ensemble mean total radiative forcing relative to 1860 rises from 2.5 w/m^2 in 2006 to about 6.4 w/m^2 in 2100 (**Figure 4**). The spread in the forcing in 2006 is related to uncertainty in the aerosol forcing.

Figures 5 and 6 show changes in global mean surface air temperature and precipitation relative to their 1861–1880 means caused by anthropogenic greenhouse gas emissions. Surface air temperature by the end of the century increases by 2.8K (2091–2100 mean) relative to pre-industrial, which is half as much as in "no policy" simulations described by Sokolov *et al.* (2009) and Webster *et al.* (2012). Most of this difference is explained by differences in emissions: the BAU scenario in Reilly *et al.* (2015) includes mitigation measures, reflecting national commitments that were created after or excluded from the "no policy" scenario in Webster *et al.* (2008). However, the surface warming in the current simulations is also 0.6K lower than in the simulations with the "Level 3" emissions scenario (Webster *et al.*, 2012) which has similar cumulative CO_2 and CO_2-equvivalent emissions to the scenario used in this paper. The differences not explained by the emissions scenario are due to the new climate parameter distributions.[3]

As mentioned in the introduction, we used a statistical downscaling approach (Schlosser *et al.*, 2013) to produce geographical distributions of changes in temperature and precipitation. Transformation coefficients used to create longitude-latitude fields from zonal values simulated by MESM (see formula (3) in Schlosser *et al.*, 2013) were calculated from simulations with 33 CMIP5 Atmo-

2 See Sokolov *et al.* (2017) for more details.

3 Compare climate parameters in Forest *et al.* (2008) to those in Sokolov *et al.* (2017).

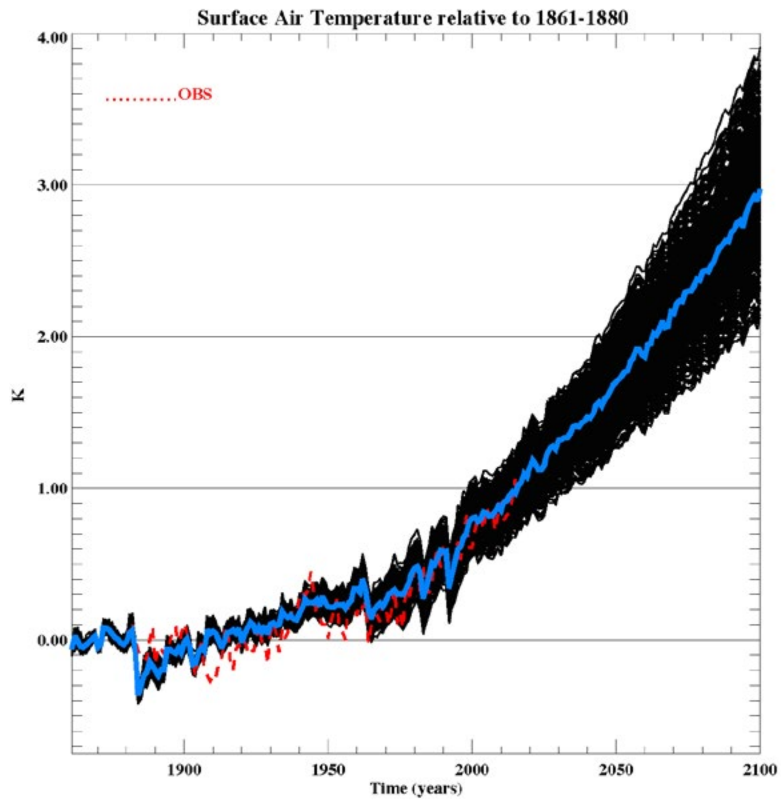

Figure 5. Global surface air temperature relative to 1861–1880. Observations are an update of the data shown on Fig. 9a in Hansen *et al.* (2010).

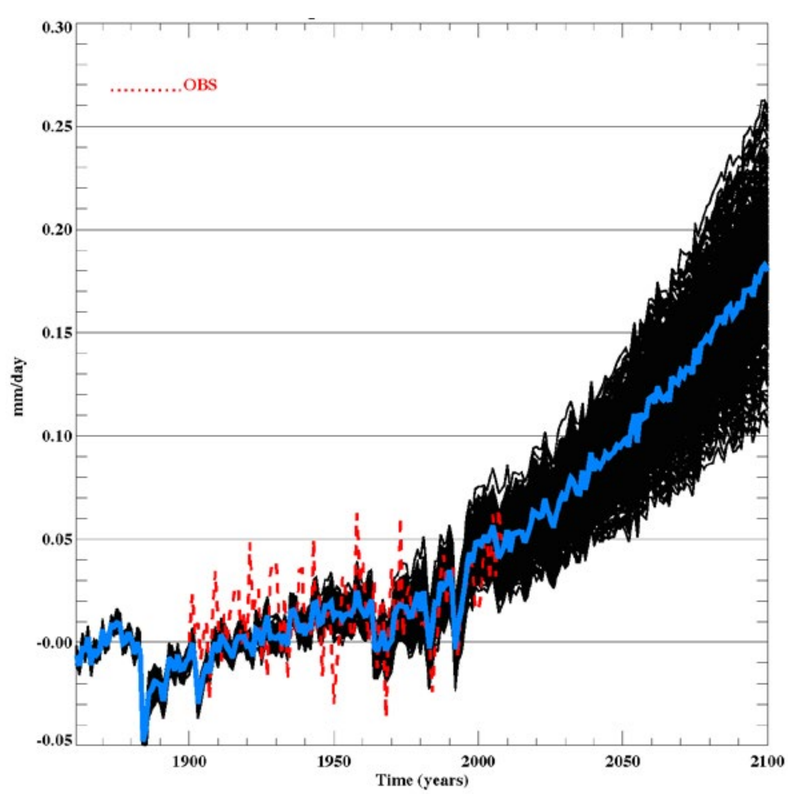

Figure 6. Global precipitation relative to 1861–1880 mean. Observations are from Smith *et al.* (2012).

sphere-Ocean General Circulation Models (AOGCMs). Using this approach, 33 different geographical patterns for each of 400 MESM simulations were produced. **Figures 7 and 8** show distributions of changes in temperature and precipitation relative to 1861–1880 averaged over all geographical patterns and all MESM runs. Unsurprisingly, the distributions obtained bear significant resemblance to the results from simulations with the CMIP5 models (IPCC, 2013 and 2014).

Using the time series of geographical distributions for temperature and precipitation thus created, we analyzed the possible climate changes over the contiguous USA. As mentioned above, uncertainty in the changes of globally averaged climate variables are defined by the uncertainty in climate system parameters, defining its response to external forcing, such as climate sensitivity and the rate of oceanic heat uptake. In the case of regional changes, additional uncertainty is coming from differences in the geographical distributions produced by different models. To

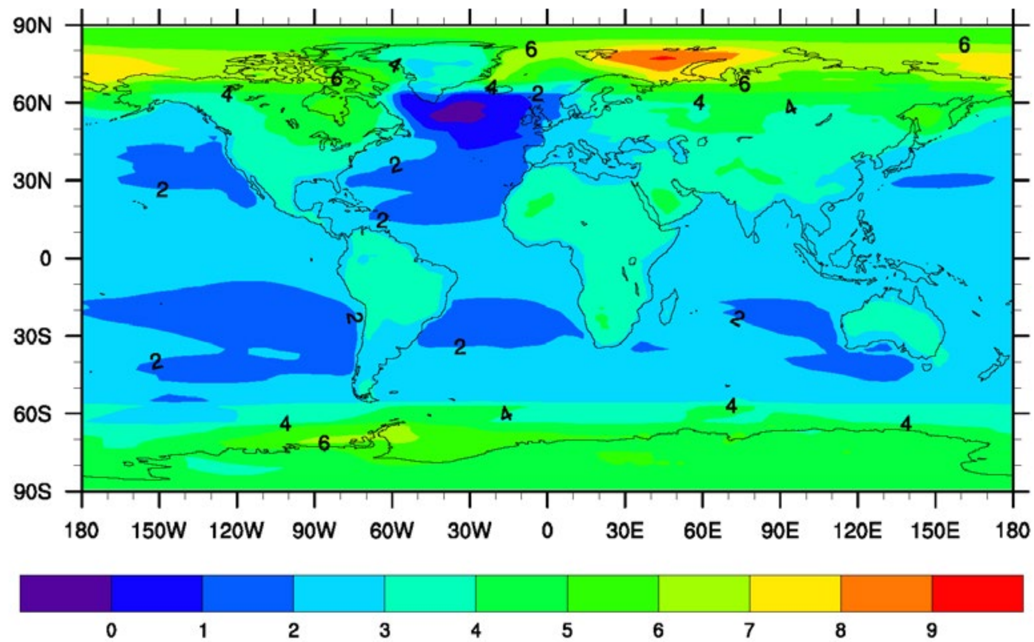

Figure 7. Surface air temperature (K) for 2091–2100 relative to 1861–1880.

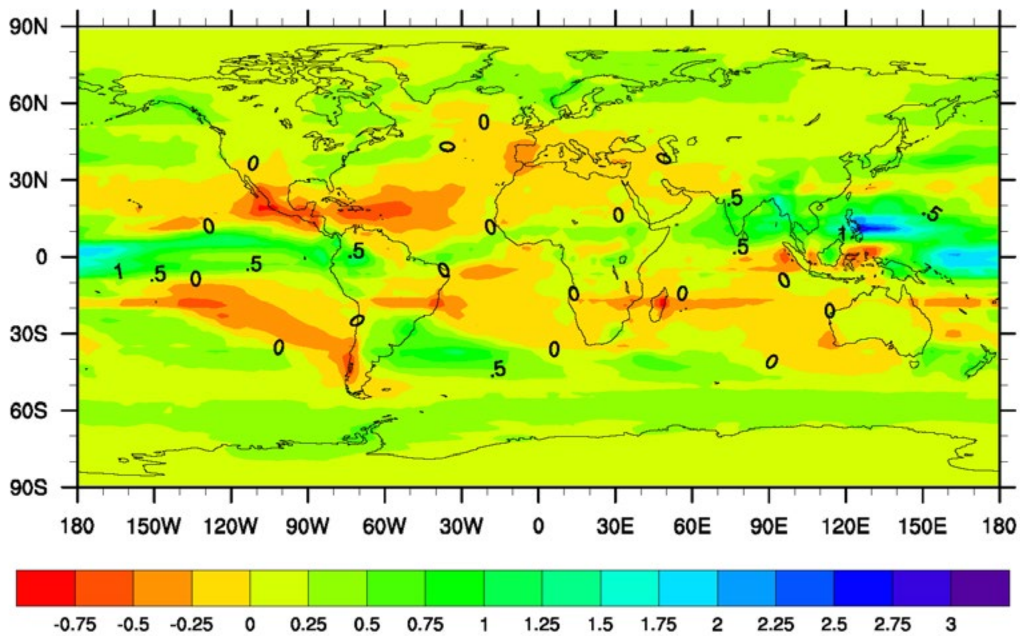

Figure 8. Precipitation (mm/day) for 2091–2100 relative to 1861–1880.

compare contributions from these sources to total uncertainty, we first averaged data for temperature and precipitation over the 400 MESM runs for each model pattern, and then over all 33 patterns for each run, i.e., for each combination of climate parameters. The former represents uncertainty associated with differences among patterns from the CMIP5 models, while the latter represents uncertainty associated with the climate parameters. As can be seen from **Figures 9 and 10**, uncertainty in surface temperature associated with the two types of uncertainty are rather similar, while uncertainty in precipitation is defined almost exclusively by differences among CMIP5 models.

As shown in Figure 10, inter-annual variability in precipitation over the USA is dramatically underestimated compared to observations. There are two reasons for this. First, the MESM underestimates variability in global precipitation (Figure 6), most likely due to use of a zonally averaged atmosphere and a simplified ocean model. Second, downscaling coefficients are calculated based on the decadal means values from observations and CMIP5

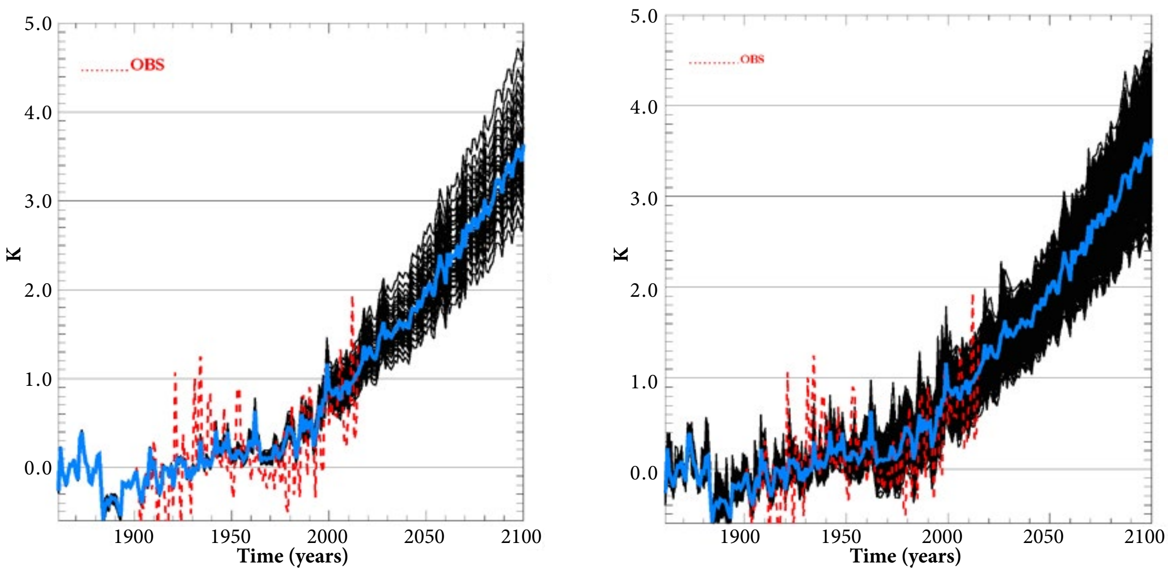

Figure 9. Surface temperature over USA relative to 1861–1880 mean. Left – averaged over runs with different values of climate parameters. Right – averaged over 33 different CMIP5 models. Observations are from Harris and Jones (2017).

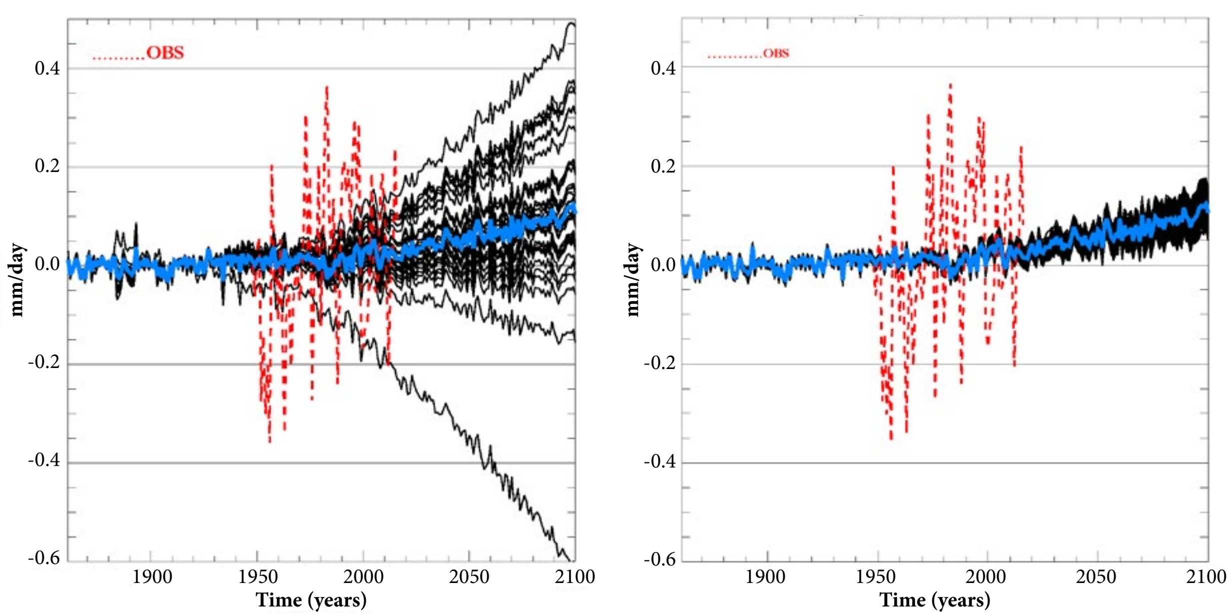

Figure 10. Precipitation over USA relative to 1861–1880 mean. Left – averaged over runs with different values of climate parameters. Right – averaged over 33 different CMIP5 models. Observations are from Higgins *et al.* (2000).

model simulations. Variability in surface air temperature is also underestimated, though to a lesser extent.

To quantify the contributions from different sources of uncertainty, we calculated global and continental USA frequency distributions for changes in surface temperature and precipitation. Distributions for the global values are calculated from the results of the 400 MESM runs. When calculating distributions for changes over the continental USA, we have eliminated the results from two outlier models. Distributions for the continental USA, shown in **Figures 11 and 12**, are based on the 400 MESM runs downscaled using patterns for 31 (33–2) CMIP5 models, which were weighted equally. In addition, we estimated 90% probability intervals using either values from the 400 MESM runs averaged over 31 models or values for 31 models averaged over 400 MESM runs. These intervals (Figures 11 and 12, **Tables 2 and 3**) provide quantitative measures for uncertainty in the predicted changes associated with uncertainty in the climate system response and inter-model differences respective-

Table 2. Percentiles for surface temperature increase relative to 1861–1880.

	5%	16.7%	50%	83.3%	95%
GLOBAL	2.30	2.52	2.82	3.14	3.40
USA ALL	2.62	2.90	3.38	3.98	4.43
USA CLIMATE PARAMETERS	2.80	3.05	3.44	3.79	4.10
USA MODELS	2.95	3.05	3.34	3.87	4.14

Table 3. Percentiles for changes in precipitation relative to 1861–1880 mean.

	5%	16.7%	50%	83.3%	95%
GLOBAL	0.13	0.15	0.17	0.20	0.22
USA ALL	-0.06	0.02	0.10	0.22	0.34
USA CLIMATE PARAMETERS	0.08	0.10	0.11	0.13	0.15
USA MODELS	-0.04	0.03	0.10	0.19	0.33

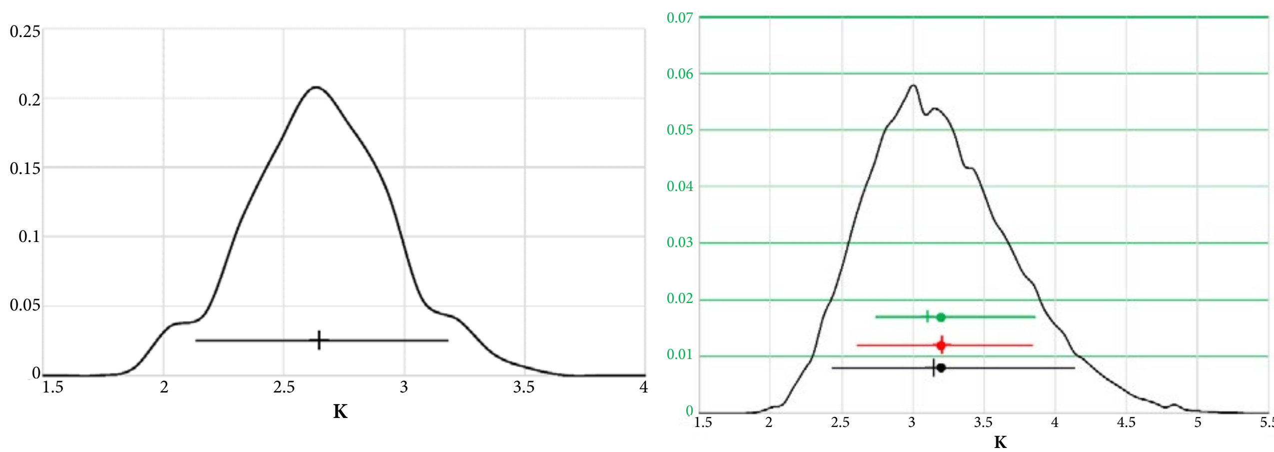

Figure 11. Frequency distributions for surface temperature over globe (left) and over USA (right) relative to 1861–1880 mean.

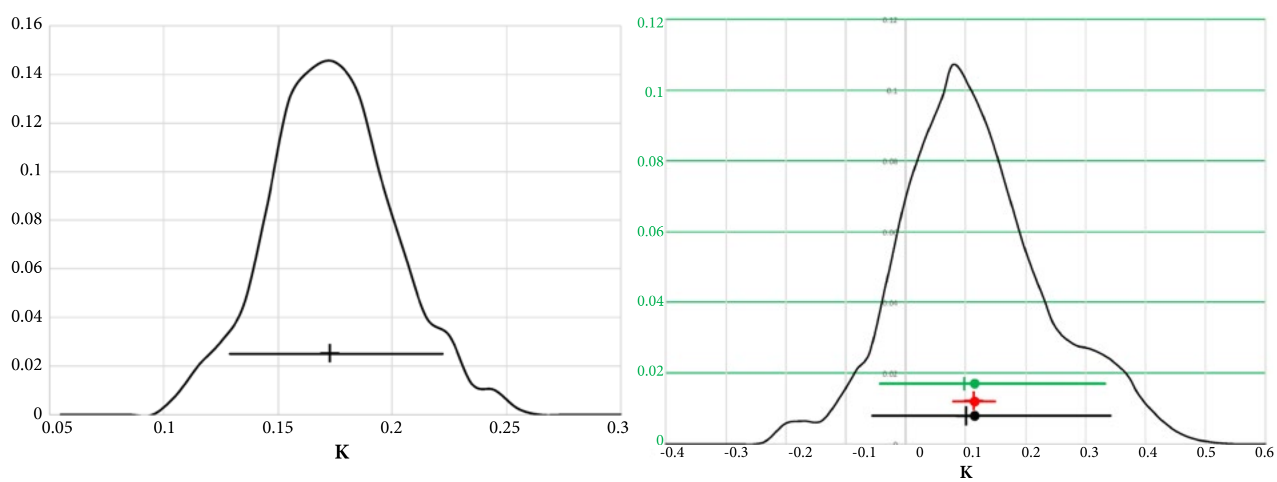

Figure 12. Frequency distributions for precipitations over globe (left) and over USA (right) relative to 1861–1880 mean.

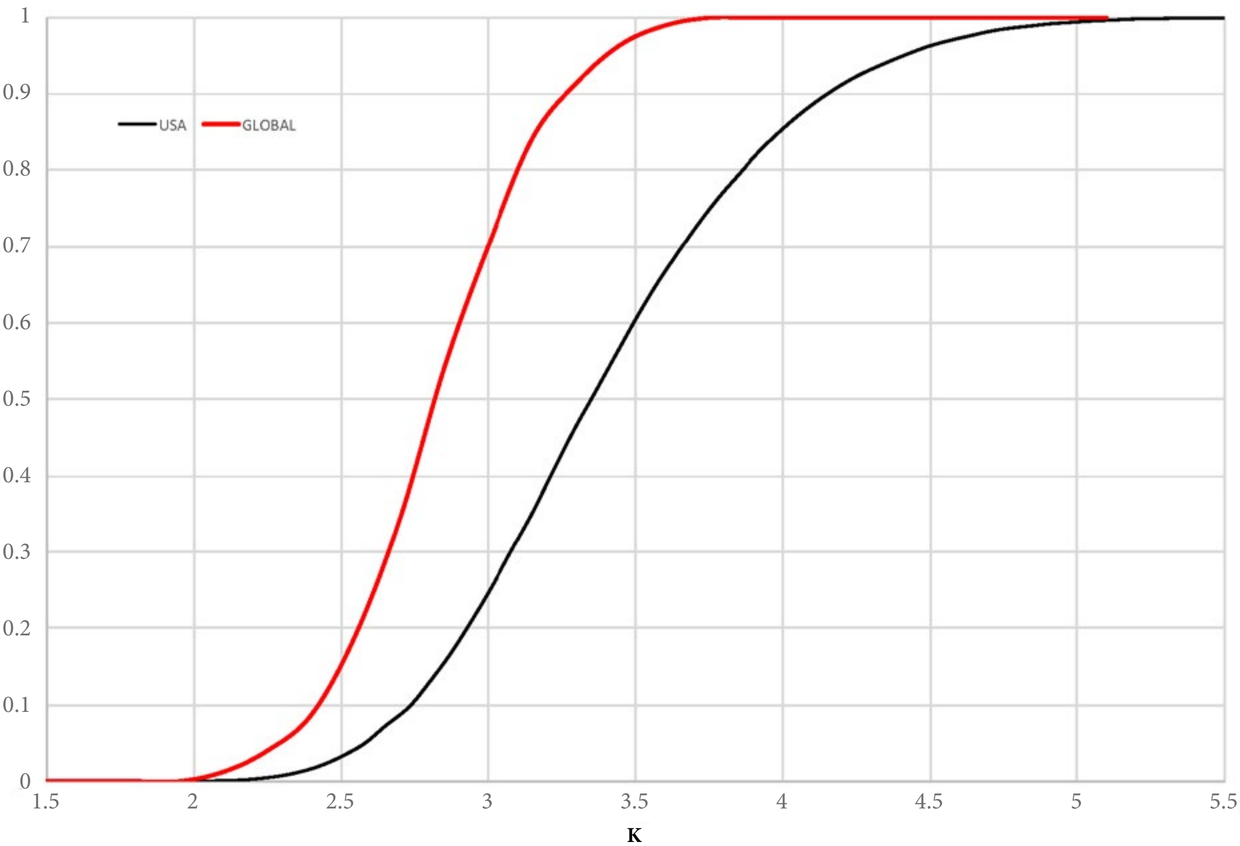

Figure 13. Probability of surface air temperature in the last decade of 21st century being below given value relative to 1861–1880 mean.

ly. The range of possible changes in precipitation over the USA is significantly wider than for the global average changes and, as noted above, it is primarily explained by the inter-model differences. Probability distributions for surface warming over the continental USA, not only shifted toward higher values when compared to distributions for the whole globe, but are also wider. While the lower bound of 90% probability interval for the USA is only 0.3K larger than for the global average, the upper bound is larger by more than 1K. As a result, the probability of surface warming staying below given a threshold is significantly smaller for the USA than for the globe as a whole (**Figure 13**). For example, while probability of the global temperature increase being less than 3°C relative to pre-industrial under the considered emission scenario is about 70%, it is only 25% for the average temperature of the USA. It is not surprising that precipitation is more uncertain for a relatively smaller geographic area than for the globe as a whole—warming will speed up the hydrological cycle and increase precipitation globally, but shifting patterns can mean that for particular regions it may increase or decrease. The enhanced warming over the continental USA reflects the general observation that land areas will warm faster than the ocean (and temperate zone location, which in general is expected to warm faster than the tropics).

Geographical distributions of changes in temperature and precipitation over the continental USA obtained using downscaling coefficients derived from the different CIMP5 models differ dramatically (**Figures 14 and 15**). While the majority of the CMIP5 models show somewhat stronger warming in the northern USA and somewhat larger increase in precipitation over the eastern states, there are noticeable exceptions. Such a diversity of CMIP5 geographical patterns indicates even larger uncertainty in the changes in temperature and precipitation on the smaller scales (e.g. states or counties). There is almost no correlation between changes in precipitation and temperature calculated using different CMIP5 model patterns (**Figure 16** and **Table 4**). For example, the *GFDL-ESM2G* pattern produces the largest increases in both temperature and precipitation. In contrast, for the *inmcm4* pattern a significant increase in temperature is coupled with a very strong decrease in precipitation. Such differences will significantly complicate attempts to evaluate climate change impacts on society, especially in sectors such as agriculture where rainfall is important.

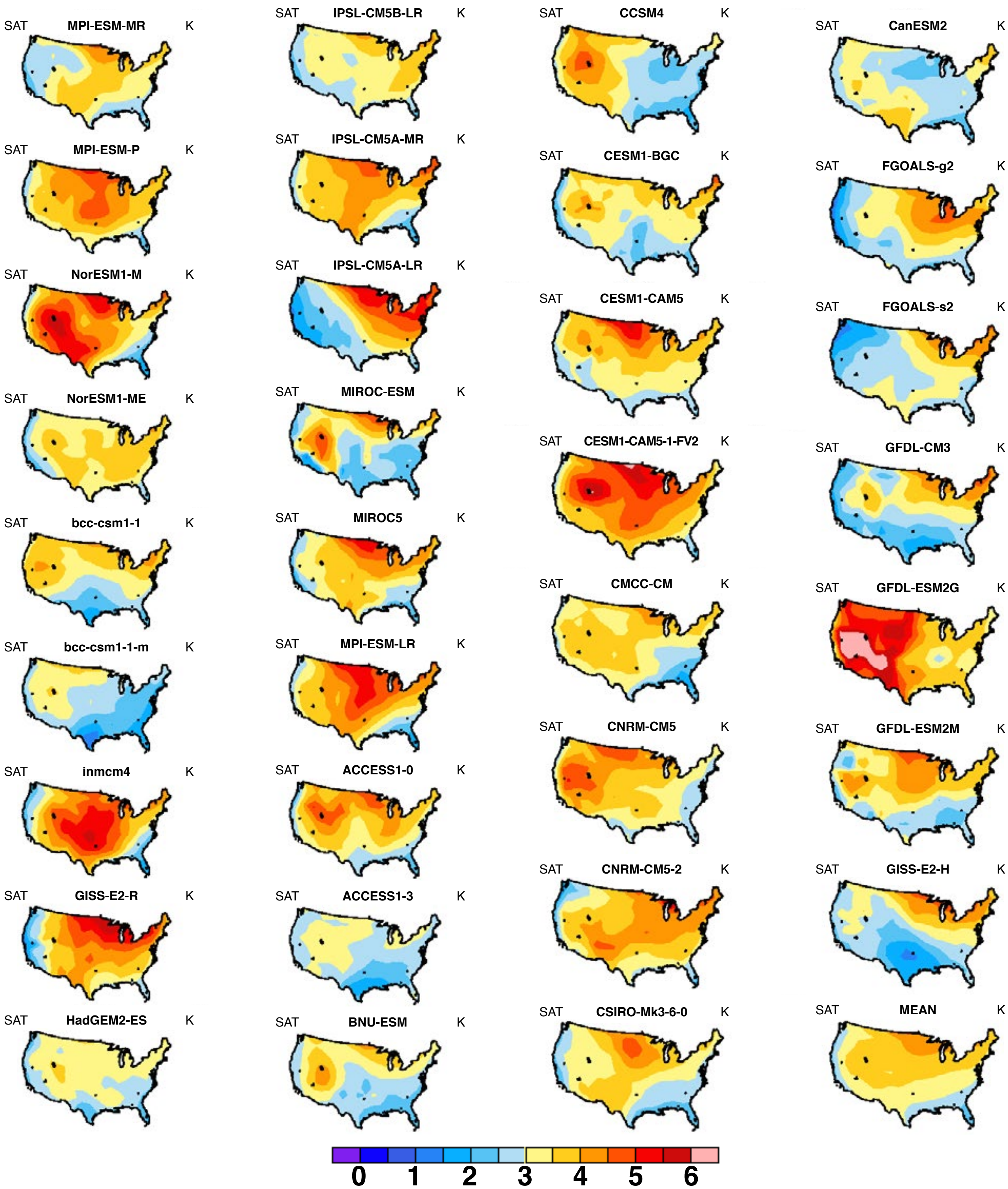

Figure 14. Surface air temperature in the last decade of 21st century relative to 1861–1880 mean downscaled using patterns from 33 CMIP5 models. Bottom right is models mean.

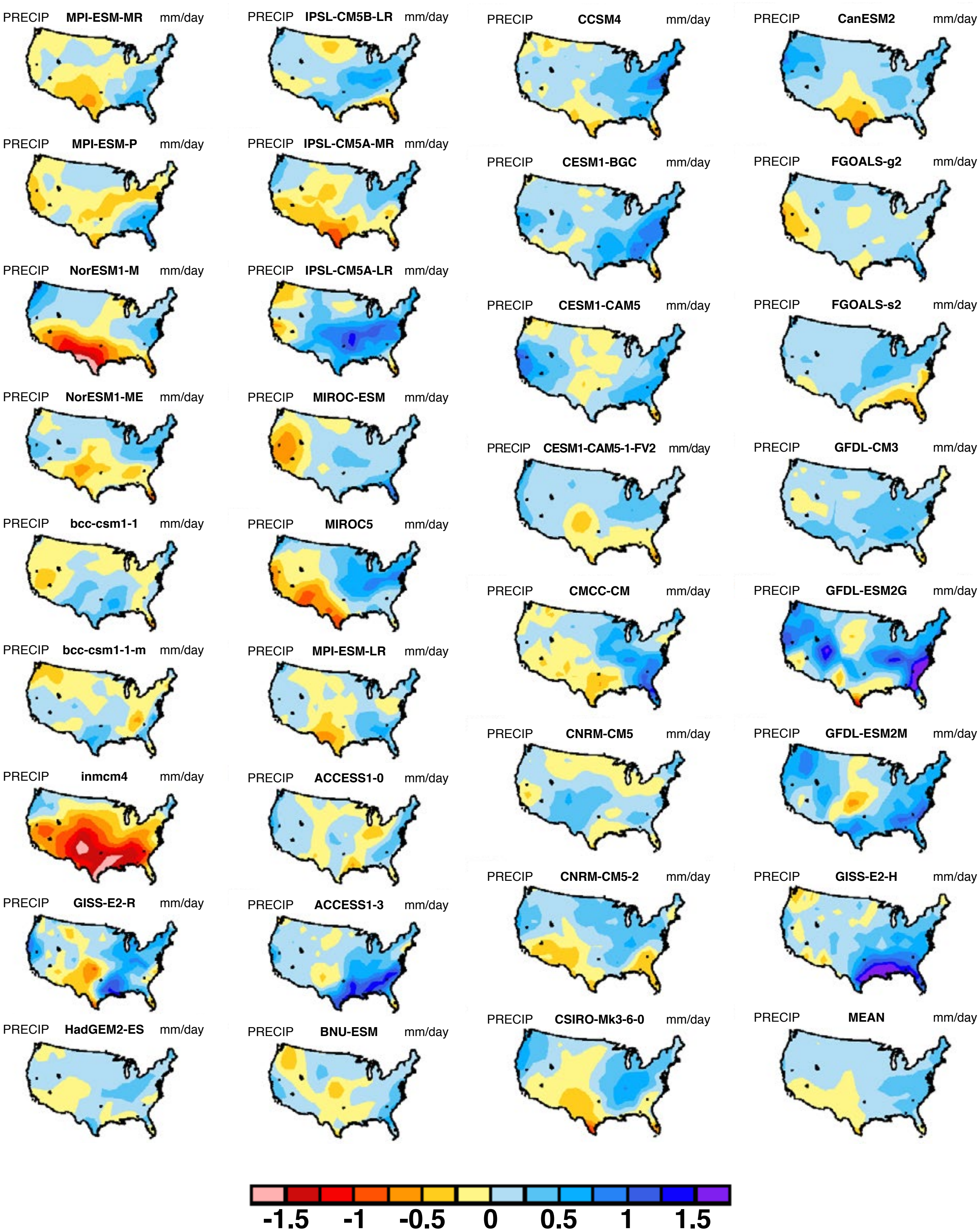

Figure 15. Precipitation in the last decade of 21st century relative to 1861–1880 mean downscaled using patterns from 33 CMIP5 models. Bottom right is models mean.

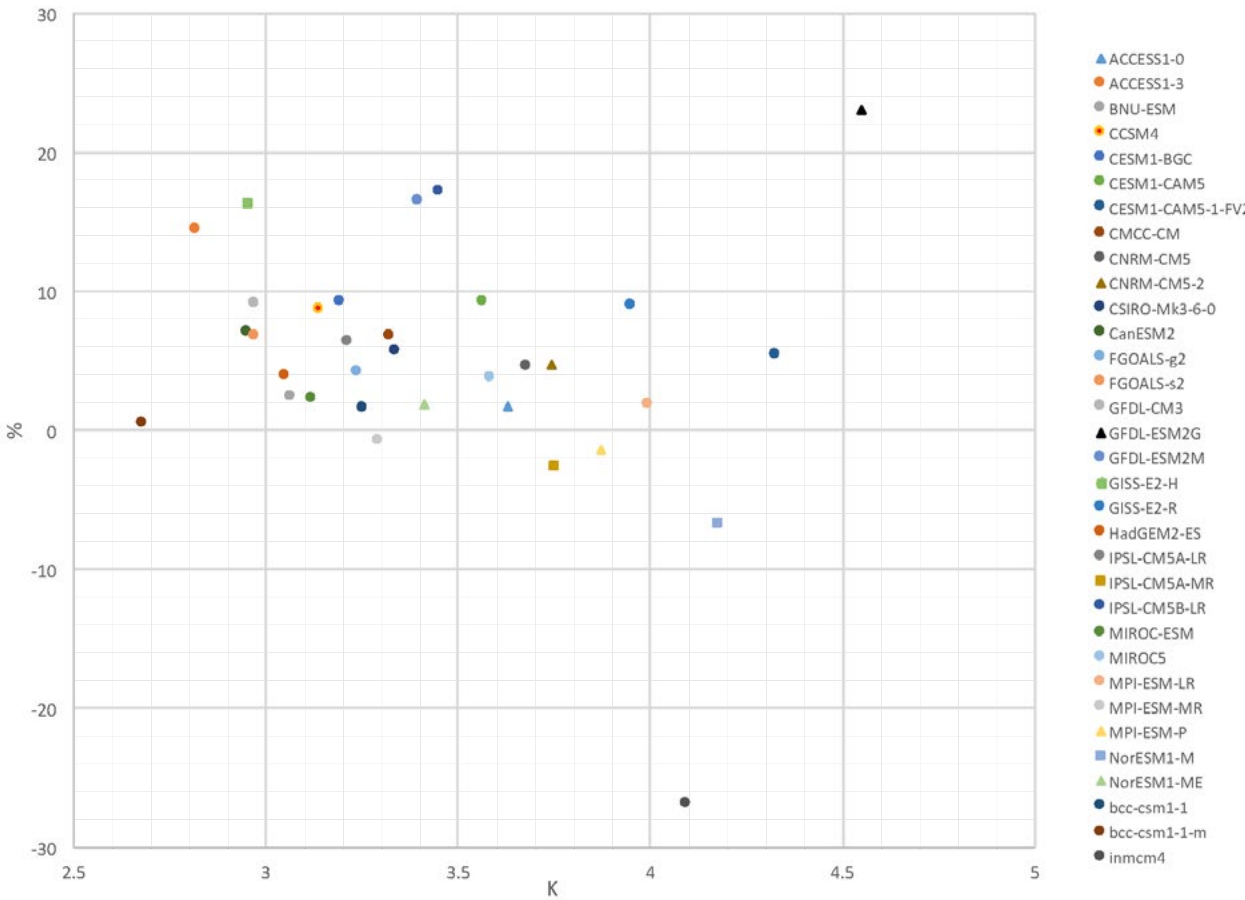

Figure 16. Changes in precipitation (as percent of 1861–1880 value) versus changes in surface air temperature averaged over USA, 2091–2100 mean minus 1861–1880 mean.

Table 4. Changes in surface air temperature and precipitation (as percent of 1861–1880 value) averaged over USA, 2091–2100 mean minus 1861–1880 mean. Models listed in order of appearance in Figure 16.

Model name	dT2m	dPrec/ Prec	Model name	dT2m	dPrec/ Prec	Model name	dT2m	dPrec/ Prec
bcc-csm1-1-m	2.68	0.4	IPSL-CM5A-LR	3.21	6.3	ACCESS1-0	3.63	1.7
ACCESS1-3	2.82	14.5	FGOALS-g2	3.24	4.2	CNRM-CM5	3.68	4.6
CanESM2	2.95	7.1	bcc-csm1-1	3.25	1.6	CNRM-CM5-2	3.75	4.8
GISS-E2-H	2.95	16.3	MPI-ESM-MR	3.29	-0.7	IPSL-CM5A-MR	3.75	-2.7
GFDL-CM3	2.97	9.2	CMCC-CM	3.32	6.8	MPI-ESM-P	3.87	-1.4
FGOALS-s2	2.97	6.8	CSIRO-Mk3-6-0	3.34	5.7	GISS-E2-R	3.95	8.9
HadGEM2-ES	3.05	3.9	GFDL-ESM2M	3.40	16.5	MPI-ESM-LR	4.00	1.9
BNU-ESM	3.07	2.5	NorESM1-ME	3.41	1.9	inmcm4	4.09	-26.9
MIROC-ESM	3.12	2.2	IPSL-CM5B-LR	3.45	17.2	NorESM1-M	4.18	-6.8
CCSM4	3.14	8.6	CESM1-CAM5	3.57	9.3	CESM1-CAM5-1-FV2	4.33	5.5
CESM1-BGC	3.19	12.8	MIROC5	3.59	3.8	GFDL-ESM2G	4.55	23.1

4. Conclusions

Under the considered emission scenario (described in Reilly *et al.*, 2015), for the last decade of the 21st century the global mean surface air temperature will increase by 2.1–3.1K (90% probability interval) relative to pre-industrial, while the temperature averaged over the continental USA is projected to rise by 2.4–4.1K. The corresponding changes in precipitation are 0.12 to 0.21 mm/day and -0.05 to 0.32 mm/day, respectively. The surface temperature averaged over the USA will exceed 3, 3.5 and 4K relative to pre-industrial with probability of about 75, 40 and 15% respectively. There is a 4% probability of exceeding 4.5K. It should be kept in mind that multi-model means for temperature and precipitation for the USA were calculated assuming with all 31 CMIP5 models weighted equally.

For a comparison with IPCC AR5 results, we calculated the difference in global mean surface air temperature between 2081–2100 and 1861–1900 periods. Under the considered emission scenario, the ensemble mean for this difference is 2.75K, which is very similar to warming under the RCP6.0 scenario (2.8K, Table 12.3 in IPCC, 2013). The 90% probability range from the MESM ensemble (2.3–3.3K) is significantly narrower than from the CMIP5 ensemble for RCP6.0 (2.0–3.7K). As noted by Sokolov *et al.* (2017), the narrower probability distribution obtained in the MESM ensemble, compared to the CMIP5 multi-model ensemble, is explained by the correlation between climate parameters imposed by the observed surface temperature changes. According to IPCC (2013), the global mean temperature, averaged over the last two decades of the 21st century, increases by more than 3K relative to preindustrial in the RCP6.0 simulations for 36% of the CMIP5 models. This threshold is exceeded in only 20% of the MESM runs. At the same time, the 2K threshold is exceeded in 100% of simulations for both the CMIP5 and MESM ensembles.

Uncertainty in the magnitude of temperature changes over the USA associated with uncertainty in the global climate system response to external forcing is comparable to the uncertainty associated with the use of the different CMIP5 model patterns. Uncertainty in precipitation change comes almost entirely from the use of different CMIP5 model patterns. Significant differences in the spatial distributions of changes in temperature and precipitation reflect the larger uncertainties inherent in changes on the smaller spatial scales.

Acknowledgments

This work was supported by the U.S. Department of Energy under grant #DE-FG02-94ER61937 and other government, industry and foundation sponsors of the MIT Joint Program on the Science and Policy of Global Change. For a complete list of sponsors and U.S. government funding sources, see http://globalchange.mit.edu/sponsors.

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77 Massachusetts Ave., E19-411
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T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/