Quantifying the Likelihood of Regional Climate Change: A Hybridized Approach

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(Manuscript received 15 December 2011, in final form 31 August 2012)

ABSTRACT

The growing need for risk-based assessments of impacts and adaptation to climate change calls for increased capability in climate projections: specifically, the quantification of the likelihood of regional outcomes and the representation of their uncertainty. Herein, the authors present a technique that extends the latitudinal projections of the 2D atmospheric model of the Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM) 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). The method maps the IGSM zonal means across longitude using a set of transformation coefficients, and this approach is demonstrated in application to near-surface air temperature and precipitation, for which high-quality observational datasets and model simulations of climate change are available. The current climatology of the transformation coefficients is observationally based. To estimate how these coefficients may alter with climate, the authors characterize the climate models' spatial responses, relative to their zonal mean, from transient increases in trace-gas concentrations and then normalize these responses against their corresponding transient global temperature responses. This procedure allows for the construction of metaensembles of regional climate outcomes, combining the ensembles of the MIT IGSM—which produce global and latitudinal climate projections, with uncertainty, under different global climate policy scenarios—with regionally resolved patterns from the archived IPCC climate model projections. This hybridization of the climate model longitudinal projections with the global and latitudinal patterns projected by the IGSM can, in principle, be applied to any given state or flux variable that has the sufficient observational and model-based information.

1. Introduction

Under the growing threat of human-induced climate change and the consequent risks to natural and managed ecosystems as well as society, there is an increasing need for regionally detailed information of important atmospheric variables (e.g., temperature and precipitation).

To meet this need, a number of issues must be addressed that involve modeling and predicting a complex system such as the earth’s climate, the uncertainty of the climate response from human forcing (e.g., Forest et al. 2006), and the assurance that the computational techniques and experimentation employed faithfully portray this uncertainty (e.g., Knutti 2010). When extending this to integrated assessments of climate change, regional climate prediction uncertainties, in addition to other uncertain aspects of the global climate system response (e.g., Forest et al. 2006) as well as emissions and their...
corresponding climate policies (e.g., Webster et al. 2012), lead to an overarching issue of “climate risk,” which impact and adaptation studies must encompass and incorporate in an increasingly quantifiable capacity.

To that end, previous assessment exercises have employed spatial disaggregation techniques so that changes in key inputs, such as temperature and precipitation, are provided at the necessary level of spatial detail (e.g., Yohe and Schlesinger 1998). Such a class of software tools has been developed over the past two decades to provide modelers with a reduced form method to explore potential climate changes under a broader range of global greenhouse gas (GHG) emissions than provided by the Intergovernmental Panel on Climate Change (IPCC) exercises. Most of these disaggregation tools have utilized pattern-scaling methods (e.g., Santer et al. 1990) to relate global mean temperature to spatial gridded impacts on temperature and precipitation based on climate model results. Additionally, analysis of the resulting global mean temperature over a range of uncertain emissions as well as climate model parameters is desirable (e.g., Sokolov et al. 2009), and so additional techniques have involved equally probable sampling of modeled information. Some examples of these tools are the Model for the Assessment of Greenhouse Gas–Induced Climate Change (MAGICC) that drives a spatial climate change scenario generator (MAGICC/SCENGEN; Wigley 2011), the Electric Power Research Institute (EPRI) second version of the Country Specific Model for Intertemporal Climate (COSMIC2; e.g., Schlesinger and Williams 1997; Schlesinger et al. 2000), and the Simulator for Climate (SimCLIM; Warrick 2009).

MAGICC/SCENGEN has been one of the primary model guidance tools used within the IPCC policy/impact arena. Its climate model is an upwelling-diffusion, energy-balance model that produces global- and hemispheric-mean temperature and also estimates oceanic thermal expansion. Global-mean temperatures from MAGICC drive SCENGEN’s pattern-scaling method (Santer et al. 1990) to produce spatial patterns of change in surface air temperature and precipitation. The pattern scaling method is based on the separation of the global-mean and spatial-pattern components of future climate change from the general circulation model (GCM) database of the IPCC’s Fourth Assessment Report (AR4; Solomon et al. 2007) archive, based on the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project phase 3 (CMIP3; Meehl et al. 2007) multi-model dataset. For the SCENGEN scaling component one can use a linear or power law (exponential; e.g., Hulme et al. 1995) to the global temperature response.

In other methods, COSMIC2 is similar to MAGICC/SCENGEN using dynamic global predictions of mean temperature with climate patterns predicted by climate models, and its outputs are provided at the country level and averages weighted by area or population. SimCLIM is an integrated modeling system for assessing climate change impacts and adaptation that uses MAGICC and a pattern matching tool, similar to SCENGEN, with CMIP3 climate models. It provides a number of extensions to the climate data provided by the MAGICC/GCM linkage to assist modelers to perform climate change impact and adaptation studies. These extensions include a set of global climate databases, tools for spatial interpolation of coarsely gridded climate change data, and statistical downscaling in some regions.

But what is absent from current methods is an ability to quantify the likelihood of particular regional outcomes, such that these outcomes can be generated under a consistent array of climate policies, modeled within a socioeconomic framework with its underlying uncertainties, and tailored to any particular policy target. Therefore, when applied to analyses on impacts and/or adaptation to climate change, information from the aforementioned approaches is limited in scope and flexibility. In this study, we present an approach that addresses this issue by applying a regional analysis capability to the Integrated Global Systems Model (IGSM; Sokolov et al. 2009). The IGS is an earth model of intermediate complexity (EMIC) linked to a multisector, multiregional model of the global economy (Paltsev et al. 2005). We present a method whereby the native frequency distributions of the IGS outputs by latitude zones are transposed across their corresponding longitudinal grids based on a method that applies a linear expansion of climate model information at the regional detail. In the section that follows, we present this approach, which includes the construction of an observation-based climatology of the downscaling patterns as well as a normalization of the climate model patterns of regional change. These steps are based on GCM ensemble results from the CMIP3 database. The resulting frequency distributions are evaluated for a select number of regions to assess their consistency with the inferred distributions from the more limited sample of the CMIP3 model collection, and further analyses evaluate the shifts in these derived distributions under a moderate climate stabilization policy. Closing remarks and directions for future work and applications are then provided.

2. Methodology
   a. Analytic formulation

The atmospheric component of the IGSM is a 2D model in altitude and latitude, and we therefore begin by
considering any latitudinal zonal (mean) field of any state or flux variable of the IGSM, \( V_{IGSM}^y \), at any given point in time. Our intent is to expand \( V_{IGSM}^y \) such that we are able to describe its variation across the latitude. We can represent this transformation as

\[
C_{x,y} = \frac{V_{x,y}^{IGSM}}{V_y^{IGSM}},
\]

where \( C_{x,y} \) is a transformation coefficient that corresponds to the longitudinal point \( x \) along any given latitude \( y \) and maps \( V_{y}^{IGSM} \) to its corresponding longitudinal value, \( V_{x,y}^{IGSM} \). While this transformation can apply, in principle, to any state or flux quantity, here the variables of interest are surface-air temperature \( T_a \) and precipitation \( P \). To calculate \( C_{x,y} \), we employ the widely used observational datasets of the Climatic Research Unit (CRU; Jones et al. 1999) and the Global Precipitation Climatology Project (GPCP) of Adler et al. (2003) for the \( T_a \) and \( P \) estimates, respectively. Each of these datasets is provided at monthly time steps, and so we build the climatological description accordingly. For any given grid point of the CRU and GPCP data, for every month of their time series, we calculate

\[
C_{x,y} = \frac{V_{x,y}^{IGSM}}{V_y^{IGSM}},
\]

to obtain a time series of the \( C_{x,y} \) coefficients. Note that the values of \( C_{x,y} \) are unitless and reflect the relative value of any given variable at a longitudinal point in relation to its zonal mean. In addition, for any variable \( V \) chosen in this estimation, it is important that the unit chosen is positive definite (i.e., kelvins for temperature), as changing values in sign cause the computation to become problematic. From this, a climatology of these transformations, \( C_{x,y} \), can be evaluated from observations. For this study, we produce a monthly climatology by obtaining averages for the period 1981–2000.

For surface-air temperature (Fig. 1), the corresponding patterns of \( C_{x,y} \) reveal an intuitively consistent seasonality. During the Northern Hemisphere winter, the relatively warmer regions of western Europe and North America—as a result of persistent maritime fetch as well as the notably colder, continental climate region of Siberia and the Hudson Bay region—are clearly distinguished. Further, warmer regions in the interior continents (e.g., Eurasia and Australia) during summer are well represented, and the persistently cooler high elevations as well as warmer desert regions are also clearly seen.

For precipitation (Fig. 2), we similarly find that the technique produces intuitively consistent and characteristic depictions of the global structure of precipitation. For example, the enhanced precipitation regions associated

\[
0.93 \ 0.94 \ 0.95 \ 0.96 \ 0.97 \ 0.98 \ 0.99 \ 0.995 \ 1 \ 1.005 \ 1.01 \ 1.02 \ 1.03 \ 1.04 \ 1.05
\]
with the preferential location of storm tracks along the western boundary of the Atlantic and Pacific Oceans are evident. In addition, the widespread desert regions are also clearly seen throughout the entire year and the progression of the intertropical convergence zone (ITCZ) is also captured.

Given these climatological constructions, we then apply this transformation to account for potential shifts or changes in climate and therefore consider that the transformation coefficients, $C_{x,y}$, may change, in a characteristic fashion, as the global system climate changes. We then expand (1) to a more comprehensive expression as a first-order (i.e., linear) Taylor expansion of $C_{x,y}$ with respect to global temperature change $\Delta T_{Global}$.

Thus, the IGSM zonal transformation process as global temperature varies can therefore be written as

$$V_{IGSM}^x \left( \Delta T_{Global} \right) = C_{x,y} \bigg|_{t_0} V_{y}^{IGSM} + \left( \frac{dC_{x,y}}{dT_{Global}} \Delta T_{Global}^{IGSM} \right) V_{y}^{IGSM},$$

where $C_{x,y} \bigg|_{t_0}$ is the transformation coefficient for any reference time period, and in our case we can equate this to the aforementioned climatological set of values, $\bar{C}_{x,y}$, based on observational data. Accordingly, $\Delta T_{Global}$ is the change in global temperature that has occurred relative to the reference or climatological period. Then, based on supporting data the derivative of these transformation coefficients, $dC_{x,y}/dT_{Global}$, for any point $(x, y)$ must be estimated. For this construction, we are particularly interested in how these transformation coefficients may vary as a result of any human-forced global temperature change. In the section that follows, the transformation coefficient derivatives are constructed from a suite of IPCC scenarios from the CMIP3 archive. In doing so, we continue our focus of this technique on two variables of interest: surface air temperature and precipitation. Evaluations are then made as to whether the derivatives represent a characteristic response in the IPCC climate model collection.

b. Regional climate change transformations

Applying the construction above, the derivative of the transformation coefficients, $dC_{x,y}/dT_{Global}$, will be estimated from GCM climate simulations forced by the scenarios from the IPCC Special Report on Emission Scenarios (SRES) as well as from the transient CO2 increase simulations ($2xCO_2$) performed by the climate model community in support of the CMIP3 exercise. These multimodel and multisenario sets of data provide an opportunity to assess whether simulated shifts are robust (across emission scenarios), and also to assess their structural uncertainty (across all the climate models). To
calculate these terms, we draw results from this model population to calculate the shifts in $C_{x,y}$ between a beginning $t_0$ and ending $t_1$ point in time:

$$\frac{dC_{x,y}}{dT} = \frac{T_{x,y}^{t_1} - T_{x,y}^{t_0}}{T_{Global}^{t_1} - T_{Global}^{t_0}}.$$ (4)

The choice of $t_0$ and $t_1$ is somewhat arbitrary but should span a sufficient amount of time such that a climate response (if any) has evolved as a result of the trends in the trace gas forcing. For the scenarios considered herein, we chose $t_0$ and $t_1$ to span the number of years at which a doubling of CO$_2$ at a transient rate of 1% yr$^{-1}$ has been achieved, equivalent to 70 years. The overbars denote that average values, at $t_0$ and $t_1$, are taken for the calculation and we used a 10-yr averaging period, starting at each reference time, $t_0$ and $t_1$. Further, the results are temporally resolved at a monthly time step, and therefore we produce a monthly climatology (based on the difference of their 10-yr means) of these transformation coefficients of regional climate change. Note that given this construction, the implicit assumption is that the $dC_{x,y}/dT_{Global}$ obtained is constant over the time period interval (70 yr). From the IPCC archive, three SRES scenarios are considered for these calculations: the A2 scenario (17 climate models), the A1B scenario (17 climate models), and the B2 scenario (17 climate models). The transient 2xCO$_2$ simulation also provides an additional collection of 19 climate model simulations from the CMIP3 exercise. We first consider the results from the A2 SRES scenario and assess the multimodel mean and scatter (standard deviation) of $dC_{x,y}/dT_{Global}$ for precipitation and surface air temperature. In the analysis that follows, all the climate model results have been bilinearly interpolated to a common $2^\circ \times 2^\circ$ resolution grid prior to any calculations.

1) TEMPERATURE

The most striking feature of the model mean $dC_{x,y}/dT_{Global}$ for $T_a$ (Fig. 3) is the resemblance of the colder ocean and warmer land (COWL) global pattern (e.g., Broccoli et al. 1998) seen in all seasons. The most notable exceptions to this characterization lie in the northernmost regions of the Northern Hemisphere land areas. Over northern Siberia, the relative cooling signal is most likely a result of thermal inertia from the snowpack and frozen soil conditions (if the climate models’ soil physics resolve this explicitly). Conversely, over the coastal regions of North America, the maritime fetch of the relatively cooler ocean conditions has a large

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Fig. 3. Global maps of the transformation coefficients, $dC_{x,y}/dT_{Global}$ (K$^{-1}$) for surface air temperature based on the CMIP3 climate models. Shown are the model-mean, seasonally averaged results for (a) DJF, (b) MAM, (c) JJA, and (d) SON.
influence. This maritime influence is also notable in
winter over Europe, the southern half of South America,
and the southeastern United States. Relatively speak-
ing, land regions where some of the largest warming
(relative to its zonal mean) occurs include South Africa,
West Africa, the Himalayan region, and the greater
Hudson Bay basin. With the exception of the afore-
mentioned relative cooling from the maritime fetch
during the winter, no seasonal features to the warming
patterns over land are discernible.

Scatter among the models in $dC_{x,y}/dT_{\text{Global}}$
indicates ubiquitously elevated values covering the bo-
real region of the Northern Hemisphere, most notably
during the winter and spring seasons. Other isolated
regions of higher intermodel scatter occur over interior
portions of South America, Australia, the Sahel, and
South Africa. Contrary to the model scatter in precip-
itation, the lowest values of model scatter occur over
much of the world’s oceans, with the lowest values con-
fined to the subtropics. Moreover, there are no striking
features in the seasonality of the oceanic minima. Con-
versely, the widespread maxima of model scatter in the
Northern Hemisphere show their southernmost extent
during the winter and northernmost retreat in the fall.
Generally speaking, land regions indicated by shades of
darkest blue and purple (i.e., $>0.001\ \text{K}^{-1}$) are regions
where the intermodel scatter is equal to or exceeding that
of the model mean value of $dC_{x,y}/dT_{\text{Global}}$. The effect of
the larger model scatter of $dC_{x,y}/dT_{\text{Global}}$ with respect to
the model mean $dC_{x,y}/dT_{\text{Global}}$ will be a broadening of the
resultant hybrid frequency distributions, which will be
presented in section 3.

2) PRECIPITATION

The model mean of $dC_{x,y}/dT_{\text{Global}}$ for precipitation
(Fig. 5) indicates a swath of drier conditions, relative to
the zonal mean, as a result of climate warming that ex-
tends from the central subtropical North Pacific into the
European continent and North Atlantic. Along this
swath, an enhanced area of relative drying is seen over
Central America and western Europe. While this drying
persists in these regions throughout most of the year, it is
strongest during the warmer months. A similar feature is
also prominent in the South Pacific basin, and extends
over the southernmost tip of South America and persists
for all seasons with an enhancement over Patagonia and
southern Argentina. The most prominent land areas of
relatively wetter conditions occur over the Asian mon-
soon region.

Generally speaking, higher degrees of scatter among
the models in $dC_{x,y}/dT_{\text{Global}}$ for precipitation (Fig. 6) are
prevalent over the world’s oceans, most notably in the
subtropical Pacific, the western boundary of the North
Atlantic, and the tropical Atlantic. The most extensive
regions of this large scatter are found in the oceanic
subtropical regions during winter and spring. Over land,
the Indian and Southeast Asian monsoon regions display the largest degree of model scatter. Other notable land areas indicating a high degree of model scatter (i.e., comparable to the mean values in Fig. 3) include the eastern half of North America, most of Central America, and the northern half of South America. A large portion of Eurasia and North Africa contains the lowest values of the intermodel deviations, particularly during the colder seasons.

3) INTERSCENARIO CONSISTENCY

The results presented in the previous section for the \( \frac{dC_{x,y}}{dT_{\text{Global}}} \) estimates were derived from the climate model simulations of the SRES A2 scenarios. Although this calculation involves a normalization of the pattern changes with respect to a unit increment of global temperature, the issue remains as to whether these (normalized) changes are robust across simulated climate projections under different GHG emission scenarios. To explore this question, we calculated the same suite of \( \frac{dC_{x,y}}{dT_{\text{Global}}} \) metrics for the A1B and B2 scenarios as well as for the 2xCO2 experiment, and obtained seasonally averaged maps of these quantities similar to those in Figs. 3–6. If the climate model responses are robust across these scenarios, we should expect a high degree of spatial consistency among their corresponding \( \frac{dC_{x,y}}{dT_{\text{Global}}} \) results. To quantify this relation, we calculated for all seasons the spatial correlation for the model-mean global fields of \( \frac{dC_{x,y}}{dT_{\text{Global}}} \) between all possible combinations of SRES and 2xCO2 scenarios. This spatial correlation calculation is then repeated using the intermodel standard deviation of \( \frac{dC_{x,y}}{dT_{\text{Global}}} \).

The results (Table 1) indicate that a high degree of spatial consistency is maintained for all seasons and between all SRES scenarios considered. This consistency is remarkably high for the surface air temperature results, with all correlations for the model-mean patterns at or above 0.96, and only a slight degradation in the correlations of the intermodel standard deviation patterns with all values at or above 0.91. For precipitation, the spatial correlations of the model mean results among all the scenarios (and seasons) are still impressive with values at or above 0.79. Similar to the results for \( T_a \), a slight degradation in the results for the intermodel standard deviation is seen, but values are still at or above 0.72. Given that the SRES scenarios are producing different rates of temperature warming for the CMIP3 models across the period of estimation (70 yr), this is largely equivalent to choosing different time periods for a given SRES scenario and thus supports the aforementioned assumption in (4) that \( \frac{dC_{x,y}}{dT_{\text{Global}}} \) can, to first order, be regarded as constant over time.

Looking at the results that include the 2xCO2 simulations (Table 2), one important caveat is revealed by the substantial decreases seen in the correlations during
the December–February (DJF) and March–May (MAM) periods. The decreases are most prominent for surface air temperature, as seen in the model mean DJF $dC_{x,y}/dT_{\text{Global}}$ results for $T_a$ from the 2xCO$_2$ results (Fig. 7). The largest discrepancy between the 2xCO$_2$ results and any SRES result (Fig. 5a shows the results for the A2 scenario) occurs in the Northern Hemisphere. The most likely cause of this result is that markedly different snow/ice albedo feedback effects are at play (both over land and ocean points) between the two simulations. Whatever the exact cause, the important caveat here is that while the SRES scenarios are consistent in their portrayal of the $dC_{x,y}/dT_{\text{Global}}$ metrics, the 2xCO$_2$ data cannot be pooled with these results. An additional point to be raised here is that regardless of these Northern Hemisphere wintertime discrepancies noted, all the simulations become consistent (high correlations) for the June–August (JJA) and September–November (SON) periods, particularly for the $T_a$ results. This suggests that the warm-season patterns of $dC_{x,y}/dT_{\text{Global}}$ are largely insensitive to the preceding wintertime conditions.

3. Hybrid frequency distributions

Given the suite of $dC_{x,y}/dT_{\text{Global}}$ values for both precipitation and $T_a$, we have a set of regional climate change kernels with which to build a metaensemble by downscaling IGSM ensemble simulations (e.g., Sokolov et al. 2009; Webster et al. 2012) according to (3). However, before undertaking this construction, we first assess

**Table 1.** Spatial correlations between the global patterns of $dC_{x,y}/dT_{\text{Global}}$ from the AR4 scenarios considered in this study (A2, A1B, and B2). Results are presented for surface air temperature and precipitation coefficients. The spatial correlations between the mean ($T_{\text{mean}}$ and $P_{\text{mean}}$) and standard deviation ($T_{\text{std}}$ and $P_{\text{std}}$) among the CMIP3 models’ $dC_{x,y}/dT_{\text{Global}}$ patterns. Results are provided for annual averages as well as for four seasonal periods: DJF, MAM, JJA, and SON.

<table>
<thead>
<tr>
<th></th>
<th>A2 vs A1B</th>
<th>A2 vs B1</th>
<th>A1B vs B1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_{\text{mean}}$</td>
<td>$P_{\text{mean}}$</td>
<td>$T_{\text{std}}$</td>
</tr>
<tr>
<td>DJF</td>
<td>0.98</td>
<td>0.84</td>
<td>0.96</td>
</tr>
<tr>
<td>MAM</td>
<td>0.98</td>
<td>0.85</td>
<td>0.96</td>
</tr>
<tr>
<td>JJA</td>
<td>0.98</td>
<td>0.90</td>
<td>0.97</td>
</tr>
<tr>
<td>SON</td>
<td>0.99</td>
<td>0.80</td>
<td>0.98</td>
</tr>
<tr>
<td>Annual</td>
<td>0.99</td>
<td>0.89</td>
<td>0.98</td>
</tr>
</tbody>
</table>

**Fig. 6.** As in Fig. 5, but for standard deviation of the transformation coefficients.
the ability of the IGSM to faithfully portray the zonal trends in \( T_a \) and precipitation. Previous work (Sokolov et al. 2010) has demonstrated that the IGSM stabilization scenarios produce global results that are aligned with climate model results from the AR4 SRES scenarios. Herein, we consider how consistent the IGSM’s zonal profiles of temperature and precipitation change are with the AR4 models, using a transient doubling of CO\(_2\) as a test case.

Figure 8a shows a pair of IGSM results with climate parameters derived separately from two ocean–heat content datasets [Domingues et al. 2008; Levitus et al. 2005; for further discussion, see Sokolov et al. (2010)]. They reveal that the IGSM’s change (increase) of annually averaged zonal \( T_a \) is well within the range of the CMIP3 climate models’ responses. In all but the southernmost latitudes, the IGSM falls within the interquartile CMIP3 range, and in those exceptions the IGSM response still lies within the minimum/maximum model responses. For precipitation (Fig. 8b), the IGSM’s change in annually averaged zonal precipitation lies within the full range of values from the CMIP3 models, yet the ubiquitous interquartile consistency, seen in the results for \( T_a \), is absent. The CMIP3 results show that for many latitude bands, the sign of the zonal precipitation change can be positive or negative, and the IGSM result shows no discernible tendency in its agreement with the majority of climate models’ sign in this regard.

Overall, compared to the majority of the CMIP3 models, the IGSM displays smaller magnitudes of precipitation change in this 2xCO\(_2\) scenario considered, which would characterize the IGSM’s zonal precipitation response (to a change in radiative forcing) as being buffered compared to the central tendency (i.e., median) of the climate model response, yet still consistent within the range of plausible climate model responses. However, the IGSM ensemble’s range of zonal anomalies [Fig. 9 shows results for the “no-policy” scenario of Sokolov et al. (2009)] does span a range very consistent with that seen in Fig. 8 for the CMIP3 GCMs. We have performed this analysis with respect to seasonally averaged quantities (not shown), which results in further support for

Table 2. As in Table 1, but based on the CMIP3 simulations of 2xCO2 experiment compared against the A2, A1B, and B1 SRES scenarios.

<table>
<thead>
<tr>
<th></th>
<th>2xCO(_2) vs A2</th>
<th>2xCO(_2) vs A1B</th>
<th>2xCO(_2) vs B1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( T_{\text{mean}} )</td>
<td>( P_{\text{mean}} )</td>
<td>( T_{\text{std}} )</td>
</tr>
<tr>
<td>DJF</td>
<td>−0.02 0.71 0.50 0.70</td>
<td>0.03 0.73 0.50 0.65</td>
<td>0.05 0.63 0.50 0.63</td>
</tr>
<tr>
<td>MAM</td>
<td>0.19 0.61 0.40 0.56</td>
<td>0.22 0.68 0.40 0.57</td>
<td>0.23 0.56 0.40 0.46</td>
</tr>
<tr>
<td>JJA</td>
<td>0.93 0.74 0.86 0.65</td>
<td>0.93 0.71 0.86 0.64</td>
<td>0.90 0.61 0.80 0.54</td>
</tr>
<tr>
<td>SON</td>
<td>0.96 0.76 0.92 0.73</td>
<td>0.96 0.75 0.93 0.70</td>
<td>0.94 0.66 0.91 0.64</td>
</tr>
<tr>
<td>Annual</td>
<td>0.85 0.85 0.76 0.78</td>
<td>0.86 0.84 0.77 0.75</td>
<td>0.84 0.79 0.74 0.70</td>
</tr>
</tbody>
</table>

![Fig. 7. Global map of the transformation coefficients, \( dC_{x,y}/dT_{\text{global}} \) (K\(^{-1}\)) for surface air temperature based on the 2xCO2 experiment of the CMIP3 climate models. Shown is the model-mean, seasonally averaged result for DJF.](image-url)
considering that IGSM’s zonal climate response is aligned with the CMIP3 model ensemble.

Given the lack of substantial inconsistencies in the IGSM’s zonal climate response as compared to the CMIP3 climate model collective, we next explore the use of (3) in constructing regionally downscaled projections. We draw from the IGSM results of Sokolov et al. (2009), which considers a no-policy climate scenario where human emissions are left unconstrained and therefore quite uncertain (as determined by the IGSM’s computable general equilibrium model of the global economy). We also draw IGSM results from an intermediate climate policy scenario: the “level 2 stabilization” (L2S) of Webster et al. (2012), which projects the twenty-first century climate as a result of a 660 ppm CO2-equivalent stabilization target at 2100. We take all 400 members from each of these ensembles and apply the complete set of $dC_{\text{z},1}/dT_{\text{Global}}$ coefficients derived from each of the CMIP3 climate models to obtain the metaensemble of outcomes. Therefore, for the cases in which we have 17 CMIP3 climate model results to draw from, such as the A2 scenario, we then assume that intermodel differences within the CMIP3 ensembles constitute an approximate (perhaps minimal) representation of uncertainty in the longitude translation, and this procedure produce a metaensemble of 6800 members. This metaensemble can then be treated as a hybrid frequency distribution (HFD) that integrates the uncertainty in the IGSM ensemble and in the (normalized) climate model ensemble of regional changes. In the next section, we apply (3) to the monthly zonal outputs of $T_a$ and precipitation to then obtain global maps of these fields. As previously mentioned (section 2b), all the downscaled results are projected onto a common $2^\circ \times 2^\circ$ resolution. While this is not necessarily a requirement for this technique, or for the use of the resulting metadata, it provides

![Fig. 8. Zonal profiles of (a) surface air temperature (K) and (b) precipitation (mm day$^{-1}$) change in response to a transient doubling of CO2 concentrations. Shown are decadal mean changes between the beginning and ending period of CO2 doubling from the IGSM as a result of two different calibrations (Sokolov et al. 2010) using different ocean heat content data. The blue dot is the IGSM result using the Domingues et al. (2008) data, and the green dot the IGSM using the Levitus et al. (2005) data. These are compared against the results from the CMIP3 climate models, which are presented as whisker plots. The red line is the median, the boxed area is the interquartile range, the dashed line spans min and max values, and red cross-hairs denote “outliers,” which are values more than 1.5 times the interquartile range away from the top or bottom of the box. The CMIP3 results presented are zonally averaged to the consistent resolution as the IGSM ($4^\circ$ latitude band widths).](image1)

![Fig. 9. Zonal profiles of precipitation change (mm day$^{-1}$) in response to a transient doubling of CO2 concentrations. Shown are decadal mean changes between the beginning and ending period of CO2 doubling from the 400-member ensemble of the IGSM from the no-policy scenario (Sokolov et al. 2009). Results are presented as whisker plots, with the endpoints denoting the minimum and maximum values, and the boxed area showing the two-standard-deviation range centered about the median value. Latitude (degrees) is provided in the abscissa.](image2)
a common (global) gridded domain for regional analysis. In the subsections that follow we construct HFDs based on area-weighted averages over selected regions of the globe. Results presented for these regions serve to highlight the interpretive capabilities of the HFDs. They also demonstrate how policy can affect these HFDs and the extent to which changes in the HFDs can be inferred as representing the odds of climate change for the region. In addition, for certain regions we compare and evaluate the degree to which these HFDs convey complementary and/or consistent diagnoses to those attributed exclusively to the CMIP3 model results. The subareas selected for detailed presentation are delineated in Figs. 3–7.

a. Southwestern United States region (SWUS)

Recent attention has been paid to the southwestern region of the United States in light of recent CMIP3 results, which indicate a consensus among climate models in drying out the region as a result of human-induced warming and, for some models, enhanced by insufficient increases in precipitation over the region (e.g., Seager et al. 2007). Looking at the no-policy case of the downscaled IGSM metaensemble, the resulting HFDs of area-averaged \( T_a \) changes over time (Fig. 10) indicate a steady warming in the mode of the distribution, reaching 3.75–4 K by the penultimate decade of the twenty-first century. The HFDs further indicate that the region will most likely experience a 1-K warming by 2030, but there is very little chance of that warming exceeding 2 K. Moving into the middle of the twenty-first century, the width of the HFD nearly doubles, ranging from possible warming outcomes of 0.75–4.5 K, with the most likely warming being about 2.5 K. The HFDs also indicate that this region could see increases or decreases in precipitation (Fig. 11), but that the chances are greater for increases with \( \approx 65\% \) of the distribution’s population in both the no-policy and the level 2 stabilization (Webster et al. 2012) scenarios. The HFD of the L2S scenario, which limits the equivalent CO\(_2\) concentrations to \( \approx 650 \) ppm by the end of the century, indicates a 0.75-K decrease in the most likely warming, compared to the no-policy scenario (Fig. 12). Further, the shift in the HFD of the L2S scenario indicates that the chances of the warmest outcomes in the no-policy scenario are removed. Similarly, the L2S scenario HFD results in shifts of the distribution’s population toward weaker precipitation increases, as seen most noticeably by a removal of any chance of the most extreme precipitation increases (Fig. 13). The L2S scenario also results in a 27% increases in the frequency of the weakest precipitation changes.
According to the IPCC AR4 results (Solomon et al. 2007), climate models convey a consensus of strong decreases in precipitation over much of Europe during the summer months (June–August) in response to human-induced warming. The median of this IPCC climate model consensus is also conveyed by the no-policy HFD (Fig. 14; 2050 conditions are compared). Exact consistency between the A2 collective and HFD is not expected, since the A2 scenario represents only one possible concentration scenario against the many possible
emission no-policy pathways as well as climate parameter and regional downscale combinations of the IGSM represented by these HFDs. Nevertheless, the bulk of the HFD population quantitatively aligns with the inter-quartile range of the 19 climate models’ A2 result. Some notable differences are that the 10% of the HFD population contains precipitation changes (at 2050) higher than the A2 result and that one of the A2 climate models [the Geophysical Fluid Dynamics Laboratory (GFDL) model] shows a much stronger decrease in precipitation than any of the HFD members. By the end of the century, the HFD indicates a slight convergence of its population, resulting in a more salient mode of precipitation change in the range of $-2.5$ to $-2.0$ mm decade$^{-1}$. This clustering of decreased precipitation is also qualitatively consistent with the A2 results (not shown); however, their clustering occurs at a lower value ($-3.5$ mm decade$^{-1}$) and could be a result of the single A2 concentration pathway and/or limited parametric and model sample. A quantitative diagnosis of the cause of these expected differences lies beyond the scope of this presentation. Nevertheless, under a similar diagnosis, we find that the results of the HFD analysis provide a depiction of the changes in global $T_a$ that aligns with the IPCC AR4 results (Fig. 15). The salient features of the HFD distributions are the occurrences of both smaller and larger increases in temperature with respect to the CMIP3 range, which would be expected (but not necessarily assured) given the larger sample size of the HFD ensemble population. A very small fraction of the distribution ($\sim 1\%$) indicates temperature changes in excess of 9 K by 2090. Conversely, less than 1% of the ensemble population indicates a warming of less than 1 K to occur by the end of the century.

\textit{c. Blue Nile region (BLNL)}

The Blue Nile region represents one of the most contentiously managed water basins of the world, with multinational upstream/downstream interests to harvest its water supply. Changes in air temperature can dramatically affect potential evaporation rates and thus the depletion of reservoirs, particularly the shallow reservoirs that cover a large surface area (such as the Aswan), and further shifts and changes in precipitation can buffer or exacerbate these conditions. The HFD results indicate that most likely this region would experience an $\sim 2$-K warming by 2050 in the absence of any climate policy, and all of the HFD populations indicate a warming of at least 0.75 K with a maximum warming of as high as 3.75 K (Fig. 16). Under the L2S scenario, the mode of the HFD reduces to a 1.25–1.5 K warming and, similar to the SWUS results, all but 3% of the entire population resides in the lower half of the no-policy HFD. Nevertheless, the stabilization scenario has little effect on the minimum warming, which remains at 0.75 K. The L2S scenario has somewhat more subtle effects on the precipitation HFD (Fig. 17). The notable shift in the mode of precipitation change indicates that the most likely increase would not be as large under climate policy. However, both scenarios show that 6%–7% of the HFD population shows decreased precipitation over the region, and that this occurrence is not very responsive to policy. Across the higher end of the precipitation change distributions, climate policy does lead to
decreases in the population bins, but only in the largest increase of precipitation does the L2S policy completely remove any chance of occurrence.

d. Yedoma region (YDMA)

Much of the soil landscape of the northernmost region of Siberia is characterized as yedoma, which signifies the carbon-rich content of the soil that extends hundreds of meters deep (Walter et al. 2006). Until recently, the soil in this region has also been locked up in a permafrost state, but recent warming over the past century and the continued warming of this region threatens a widespread thawing and subsequent adverse consequences to infrastructure, such as gas pipelines (e.g., Paltsev 2011) and potentially strong biogeochemical feedbacks to the climate system (Zhuang et al. 2006). We focus our HFD analysis on a core area of the yedoma region (denoted by the YDMA box in Figs. 3–7), where some of the coldest conditions and richest soils exist (Walter et al. 2006). By the middle of this century, the HFD results indicate that the most likely warming will be in the range of 3.25–3.5 K, and that 50% of the HFD population lies above this warming (Fig. 18). At this warming rate, half of the total permafrost area of the pan-arctic region will have thawed (e.g., Lawrence and Slater 2005), with nearly complete degradation by the end of the twenty-first century. The largest warming that this region could experience (by 2050) is in the range of 5.0–5.25 K. Under a moderate climate policy, nearly all of the HFD population lies below this degradation situation. Moreover, the mode of the distribution has decreased by 1 K.

e. Amazon region (AMZN)

With its rich biodiversity, ubiquitous rain forest conditions undergoing extensive deforestation, and the largest outflow of freshwater into the world’s oceans, the Amazon River basin is among the most compelling watersheds of the global environment. Changes to this environment, whether a direct consequence of human activities (i.e., deforestation) or a result of a global climate shift, are of paramount importance. One striking aspect of the HFD of precipitation (Fig. 19) for this region is the large spread of change for the region, both positive and negative. Overall, the positive changes reach a higher magnitude (about doubled) than the negative among the HFD population, and the mode of the distribution lies in positive precipitation change (~3.0 mm decade⁻¹). The effect of policy is subtle, but it
causes a notable shift in the skewness of the distribution with the population of the highest precipitation increases diminished. This, in turn, causes the mode value of precipitation increase to diminish to \(\sim 1.5 \text{ mm decade}^{-1}\), but the peak of the distribution is broad and ranges from 1.0 to 2.5 mm decade\(^{-1}\). The occurrence of decreases in precipitation is slightly enhanced, but they are not as extensive as seen in the precipitation increases.

**f. Southeastern Australia region (SEAU)**

Australia can be characterized, geographically speaking, as being dominated by harsh, arid conditions in its interior continental regions. One region in contrast to this is the southeastern region (Figs. 3–7) with its relatively cooler conditions (Fig. 1) and higher rates of precipitation (Fig. 2) throughout most of the year; it also contains a substantial portion of the country’s population. By the middle of the twenty-first century, and in the absence of any stabilization policy, the central tendency of the IGSM HFD indicates a 1.5–1.75-K warming, and nearly 75% of the distribution lies within the range of 1.25–2.0 K (Fig. 20). About 3% of the distribution results in the warming of less than 1 K, and less than 1% of the metaensemble’s population indicates a warming of greater than 3 K. Through the level 2 stabilization scenario, the central tendency of warming declines by 0.5 K (or a 33% reduction), and the fraction of the ensemble population that immediately flanks the mode increases. Under policy, the skewness of the HFD is affected somewhat such that a slightly smaller portion of the model population lies above the mode value of warming (32% for no policy compared to 25% for the L2S).

For precipitation (Fig. 21) the structure of the HFDs between the no-policy and L2S scenarios are more skewed and less cohesive than that of temperature. For the no-policy HFD, the model population shows that, generally speaking, both increases and decreases of precipitation could be seen over the region, and as such, the shape of the distribution is bimodal. However, the HFDs are able to characterize the probabilistic nature of these decreases and increases quite differently. The increases in precipitation exhibit a much more pronounced tail in the distribution and indicate slight occurrences (1%–2% of the model population for each bin) that are double in magnitude to any of the decreases. The distribution of decreased precipitation exhibits more of a clustered behavior, with distinct occurrences of values in the range of \(-3.0\) to \(-2.0 \text{ mm decade}^{-1}\). The largest fraction of the model population occurs in the \(-1.0\) to \(-0.5 \text{ mm decade}^{-1}\) range. Notwithstanding these distinctly different features between positive and negative regions of the distribution, the HFD is only slightly skewed with
respect to the sign of precipitation change, with 42% of the population showing decreases and 58% of the population with increases. Under climate policy, occurrences of the highest changes are buffered (or removed) and shifted toward lower values. With these shifts, the minimum and maximum values of the precipitation-change distribution decrease by about 15%. This also results in a more pronounced bimodality about the median of the distribution; in particular, the decrease precipitation feature becomes more salient compared to its increase counterpart.

g. South Africa region (SAFR)

According to the IPCC AR4 results (Solomon et al. 2007), a substantial fraction of the climate models indicate widespread decreases in precipitation. Yet in
studies using regional methods, the results are mixed, with both decreases and increases in precipitation projected under human-forced change (Thomas et al. 2007). The HFDs of the IGSM metaensemble indicate a mixed situation for precipitation changes (Fig. 22), with a nearly equal distribution of both increases and decreases in precipitation with 42% versus 58%, respectively, for the no-policy case (thus a slightly greater chance for decreased precipitation). Further, there is a slight skewness to the distribution in that a small number of the population members achieve increased precipitation values that exceed, in magnitude, any decreases in precipitation. The impact of policy is subtle, but the most notable effect on the HFD is seen in the reduction of the occurrence of the most extreme changes; in particular, the largest change in precipitation increase seen in the distribution is reduced by 33% (from 3 to 2 mm decade$^{-1}$). These reductions in the occurrence of the largest changes then directly contribute to a more pronounced mode in the HFD, but the location of the mode (a small decrease) is unchanged.

![Fig. 18.](image1.png)

![Fig. 19.](image2.png)
4. Closing remarks

We have presented a technique that transforms the zonal information of the IGSM on climate variable trends into longitudinal detail. This is achieved through a linear (Taylor) expansion of the changes in the longitudinal patterns (normalized by its respective zonal mean) as a function of global temperature change. These pattern shifts are derived from model results from the IPCC AR4 SRES scenarios, and then normalized with respect to their climate sensitivity. We have constructed monthly climatologies of these climate change patterns from the CMIP3 archive and have found that for any given climate model these derived pattern changes are robust across all of the SRES scenarios considered. With the entire CMIP3 model collective, we can combine each of these climate change pattern transformations to all of the ensemble simulation members of the IGSM that have been produced for climate policy analysis, which then enhances the spatial details of the IGSM. Combined, these augmented simulations form the basis for “hybrid frequency distributions” (HFDs) for any particular region.
Several underlying assumptions and limitations to this HFD approach must be noted. First, the procedure cannot, strictly speaking, be regarded as an emulator for a specific GCM. Rather, the intent of the presented approach is to encapsulate the uncertainties of regional climate change outcomes, as inferred by the Taylor expansion procedure performed on the CMIP3 archive. Additional GCM experiments, such as those conducted in conjunction with the IPCC Fifth Assessment Report could, undoubtedly, provide a more comprehensive assessment in this regard. A more comprehensive description may also be achieved (and is perhaps necessary for some variables) by considering a higher-order Taylor expansion. Indeed, the results for precipitation indicate that beyond a particular time horizon, a higher-order expansion may be necessary to rectify underrepresentative results (e.g., Figs. 11 and 14). Further, the procedure is limited in its omission of the effects of aerosols and other nongreenhouse gas effects (e.g., land cover change). This is not a reflection of the limitation in the analytic formulation per se, but rather the unavailability of climate model output that would allow such a quantitative dissection of this effect. The procedure, as presented, might also be viewed as limited in its treatment of \( \frac{dC_x}{dT_{\text{Global}}} \) as constant for a given climate model, and in that changing a given climate model’s climate sensitivity may, in fact, change our corresponding estimate of \( \frac{dC_x}{dT_{\text{Global}}} \). However, recent evidence (Sokolov and Monier 2011) shows that changing a climate model’s climate sensitivity, but not the structure of its parameterizations, does little in the way of affecting its simulated
patterns of regional climate change (particularly temperature and precipitation). Thus, by spanning the range of structural uncertainty in GCMs through the use of the CMIP3 archive, we believe we are addressing the first-order causes of this uncertainty.

Recent studies with the IPCC AR4 archive have focused on the apparent need to filter and/or weight certain climate model according to a chosen skill metric (e.g., Shukla et al. 2006) and the general effects that filtering has on the resulting analyses (e.g., Weigel et al. 2010). Some of these efforts were motivated either by computational constraints of vetting the data through impact models or for the purpose of highlighting the more “reliable” results and implying that these modeled outcomes were, in a sense, “more likely.” More recent model analyses have emphasized that caution must be taken in the interpretation of model skill in this regard (e.g., Knutti et al. 2010; Reifen and Toumi 2009). Any filtering in this regard will undoubtedly be a complex function of the variables of interest, their use, their temporal frequency, the region/domain of focus, the skill/filtering metric(s) chosen, the time period of interest, and the climate events and/or phenomena that are of particular concern as well as the important spatiotemporal scales in this regard. Given these issues, this study makes no deliberate attempt to filter out any modeled outcomes and, as such, considers all members of the HFD metaensemble equally. Recent analyses support equal weighting as robust, particularly in the absence of any comprehensive quantitative description of climate model performance (e.g., Weigel et al. 2010; DelSole et al. 2013). Nevertheless, our ongoing efforts are exploring the use of Gaussian quadrature techniques (e.g., Arndt et al. 2006) to limit the metaensemble size, while preserving the statistical moments of key parameters, prior to its application in impact and/or adaptation assessments. The downsized ensemble would therefore reduce computational demand while preserving the scope and character of the resulting impact/risk assessment. Notwithstanding these issues, to quantify the true climate risk and societal implications of these HFDs, the transformed IGS variables require further vetting through impact assessment models. These presented variables, as well as other atmospheric variables of interest, can be produced for any domain of interest for an appropriate climate-scale grid (e.g., $2^\circ \times 2^\circ$). Our downscaling efforts with the IGS are ongoing and a future paper will assess the feasibility of employing higher-resolution regional climate model projections, such as those from the recent North American Regional Climate Change Assessment Project (NARCCAP; Mearns et al. 2009), to provide these HFDs at even greater regional and spatial detail.

**Acknowledgments.** This work was funded by the U.S. Department of Energy’s Abrupt Climate Change program, Grant DE-FG02-08ER64597. The authors also gratefully acknowledge additional financial support for this work provided by the MIT Joint Program on the Science and Policy of Global Change through a consortium of industrial sponsors and federal grants. Development of the IGS model applied in this research was supported by the U.S. Department of Energy, Office of Science (DE-FG02-94ER61937), the U.S. Environmental Protection Agency, EPRI, and other U.S. government agencies and a consortium of 40 industrial and foundation sponsors. For a complete list see http://globalchange.mit.edu/sponsors/all. We also acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP’s Working Group on Coupled Modelling (WGCM), for their roles in making available the WCRP CMIP3 multimodel dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy. The authors would also like to thank Henry Jacoby for his valuable discussions and editorial remarks in earlier versions of this manuscript.

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