A Simple Equation for Regional Climate Change and Associated Uncertainty

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ABSTRACT

Simple equations are developed to express regional climate changes for the twenty-first century and associated uncertainty in terms of the global temperature change (GTC) without a dependence on the underlying emission pathways. The equations are applied to regional temperature and precipitation changes over different regions of the world, and relevant parameters are calculated using the latest multimodel ensemble of global climate change simulations. Examples are also shown of how to use the equations to develop probability density functions (PDFs) of regional climate change based on PDFs of GTC. The main advantage of these equations is that they can be used to estimate regional changes from GTC obtained either from simple and intermediate complexity models or from target CO2 stabilization concentrations.

1. Introduction

It is a remarkable property of the climate change signal simulated by current atmosphere–ocean general circulation models (AOGCMs) that various surface climate variables show regional patterns of change that are very similar across different scenarios and time slices (e.g., Mitchell et al. 1999; Mitchell 2003; Räisänen et al. 2004; Giorgi 2005a). Among such variables are mean surface air temperature and, somewhat to a lesser extent, precipitation. Although the patterns of change are similar across the scenarios, the magnitude of the changes tends to increase monotonically with the greenhouse gas (GHG) forcing and the globally averaged temperature response. This feature underlies the so-called pattern-scaling method (Mitchell et al. 1999; Mitchell 2003), a tool used to produce regional climate change information based on a limited number of global model simulations and scenarios.

What makes this scaling behavior particularly remarkable is that it seems to hold relatively well, even if the emission scenarios have quite different regional features, such as the emission and distribution of atmospheric aerosols. It also seems to hold across a relatively wide range of GHG concentrations and global temperature responses regardless of the underlying emission pathways, especially when the change signal is strong (Giorgi 2005a). Therefore, this robust monotonic dependence would suggest that global temperature change (GTC) might be used as either an independent variable or a predictor for regional climate change.

This would give us a powerful tool for regional climate change prediction in different ways. First, the prediction of regional change would be independent of specific aspects of the underlying emission scenarios and it would only be tied to the global temperature response. This would allow us, for example, to estimate regional changes based on assumptions concerning the GTC without having to account for underlying assumptions on the corresponding emission pathways. Second, results from simple or intermediate complexity models could be used to directly infer regional changes in relevant climatic variables. As a result, for example, probabilistic predictions of regional climate change could be estimated from probabilistic predictions of GTC, based on the use of simplified climate models (e.g., Wigley and Raper 2001; Andronova and Schlesinger 2001; Webster et al. 2003; Mastrandrea and Schneider 2004).

On the basis of these considerations, in this paper a simple equation is developed to express the changes in regional surface climate variables for the twenty-first century in terms of the GTC. In addition, a corresponding equation is developed to relate the uncertainty of the regional change to the GTC. This adds important
information concerning the predictive value of the regional change equation. The regional climate variables considered here are mean surface air temperature and precipitation, and the parameters of the predictive equations are estimated from the latest set of AOGCM simulations performed in support of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report, and stored at the Program for Climate Model Diagnosis and Intercomparison (PCMDI; available online at http://www-pcmdi.llnl.gov). This dataset is here referred to as the Multi Global Model Ensemble (MGME).

To illustrate the behavior of the proposed equations, they are applied to twenty-first-century climate change projections for the northern Europe (NEU) and Mediterranean (MED) regions as defined by Giorgi and Bi (2005). The values of relevant parameters for 26 land regions worldwide are, however, also provided. Finally, examples are shown of the use of this methodology to produce probability density functions (PDFs) of regional temperature and precipitation change based on PDFs of GTC.

Section 2 first presents a description of the methods and datasets used in this study. Results from the application of the method to the northern Europe and Mediterranean regions are shown in section 3, while section 4 presents relevant parameters calculated for 26 regions worldwide. Section 5 describes the use of the method to produce PDFs of regional changes, while summary considerations and recommendations for future work are presented in the concluding section 6.

2. Methods and datasets

a. The equations for regional climate change and related uncertainty

We here develop equations in which the change in a regional climate variable is expressed as a function of the GTC (also referred to as \(H9004\)). The equations for regional climate change and precipitation change based on PDFs of GTC. The overall uncertainty in the estimate of the transfer function \(F_{(T,P)}(\Delta Tg)\) is thus given by

\[
\sigma_{F_{(T,P)}}(\Delta Tg) = [\sigma_{IM,(T,P)}(\Delta Tg)^2 + \sigma_{IV,(T,P)}(\Delta Tg)^2]^{0.5}, \tag{2}
\]

where it is assumed that the two sources of uncertainty are independent of each other. All of the quantities in Eqs. (1) and (2) are calculated from the MGME simulations as illustrated in section 3. The MGME is described in section 2b. Note that all the functions in Eqs. (1) and (2) depend only on the GTC and not on the particular emission pathway that leads to a certain value of GTC. This is the key assumption underlying the use of our proposed approach and it is valid to the extent that the regional patterns of climate change scale with the GTC. Therefore, to the extent that this assumption is valid, the GTC can be considered as an effective predictor for regional temperature and precipitation change. The validity (or, better, the lack of validity) of the scaling assumption is measured by the uncertainty defined by Eq. (2). When this uncertainty is greater than the ensemble average signal, Eq. (1) cannot be expected to have a predictive value.

b. Datasets and illustrative cases

The MGME used here is described in Table 1. It includes 19 models from laboratories around the world spanning a relatively wide range of resolutions, from
Table 1. List of models and simulations used in this study. See the PCMDI Web site for more information.

<table>
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<th>B1</th>
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*Note that two of the original MGME models are neglected [the Flexible Global Ocean–Atmosphere–Land System (FGOALS) and Beijing Climate Center (BCC) models] because of their poor performance in simulating the climate of the European region, which is used here for our illustrative cases (see below).*

The changes in climate variables are here calculated for periods of 20 yr. This length of period is sufficient to filter out interannual variability (e.g., resulting from ENSO) but to retain multidecadal variability. The twenty-first century is thus first divided into five consecutive 20-yr periods (2001–20, 2021–40, 2041–60, 2061–80, 2081–2100). Changes are then calculated as the difference between the mean temperature and precipitation for each of these periods and the period of 1961–80, which is chosen as reference because it is the latest 20-yr period in the twentieth century in which the anthropogenic signature is relatively minor (Houghton et al. 2001). Our conclusions, however, do not depend on the choice of the twentieth-century reference period. When multiple realizations of the twentieth-century simulation are available for a given model, the reference period model climatology is calculated as the ensemble average of all available realizations.

We here consider changes in mean surface air temperature and precipitation calculated for the 26 regions, wet seasons, and dry seasons as defined in Table 1 of Giorgi and Bi (2005). For illustrative purposes we discuss in detail results only for the MED (30°–47°N, 10.5°W–37.5°E) and NEU (47°–70°N, 10.5°W–27.5°E) regions. Based on the CRU climatology, in the Mediterranean the wet season is October–March (ONDJFM) and the dry season is April–September (AMJJAS), while over northern Europe AMJJAS is the wet season and ONDJFM is the dry season (Giorgi and Bi 2005). The regional averages include only land points in the CRU-based land mask grid. These two regions were chosen to be particularly representative because they show large changes for both temperature and precipitation and different signs of the precipitation change [positive in northern Europe and negative in the Mediterranean; see below and Giorgi and Bi (2005)]. Indeed, Giorgi (2006) places these regions among the most prominent climate change hot spots.

### 3. Results for the Mediterranean and northern Europe regions

Figures 1 and 2 show the dependency of northern Europe and Mediterranean wet and dry season temperature and precipitation change on the GTC.
Changes for the five 20-yr periods of the twenty-first century with respect to 1961–80 (see section 2b), including all models and scenario simulations, are reported in the scatterplots and, when multiple realizations are available, the ensemble average of the changes is used. These figures indicate warming in all cases, decreased precipitation over the Mediterranean in both seasons, increased precipitation for the NEU ONDJFM case, and a mixed signal in the NEU AMJJAS case. They give two important messages. First, both for temperature and precipitation, the monotonic dependence of the regional change on the GTC appears to be robust. The only exception is the NEU AMJJAS precipitation change case, in which this monotonic dependence is not present when looking at the overall ensemble, although it is present in individual models. In this case the MGME does not indicate a clear compounded precipitation change signal (Giorgi and Bi 2005), and in fact, as we will see below, the uncertainty is much larger than the signal. The second message is that it is essentially impossible to distinguish between different scenarios in terms of the dependency of the regional change on the GTC. This supports the approach of using the GTC as an independent predictor variable, regardless of the underlying emission pathway.

To verify this assumption we calculated the linear trend values between the GTC and the regional changes of Figs. 1 and 2 for the three scenarios separately and when compounding all of the scenarios together. For temperature the slopes of the trend lines varied by less than 10% between the individual and compounded scenarios. For precipitation they varied by less than 28% in the three cases where a clear relationship is found (MED AMJJAS, MED ONDJFM, NEU ONDJFM), while it was very large for the NEU AMJJAS case in which a clear change signal is not found. This indicates that the basic assumption underlying Eq. (1) is robust for the temperature change, while it is more uncertain for precipitation. The uncertainty related to this assumption is measured by Eq. (2), as shown below.
The regional changes in Figs. 1 and 2 can be replotted as a function of $\Delta(T, P)/\Delta T_g$, that is, as a function of $F_{(T,P)}(\Delta T_g)$ in Eq. (1). The resulting scatterplots are shown in Figs. 3 and 4. They show “Christmas tree”–like distributions by which the simulation spread is at a maximum for small values of GTC and decreases with increasing GTC. The Christmas trees are mostly vertical, indicating that, on average, the function $F_{(T,P)}(\Delta T_g)$ remains nearly constant with respect to the GTC, except for the NEU ONDJFM temperature change case (Fig. 3), in which a slight tilt appears. In this case, $F_{T}(\Delta T_g)$ is evidently a decreasing function of the GTC. The noticeable exception in Figs. 3 and 4 is again the case of the NEU AMJJAS precipitation change in which, as already discussed, the MGME does not give a clear compounded signal.

To calculate the compounded values of $F_{(T,P)}(\Delta T_g)$ and $\sigma_{IM,(T,P)}(\Delta T_g)$ from the MGME the following procedure is used. Given that the number of points in the scatterplots of Figs. 3 and 4 is not large, the full range of simulated GTC is divided into relatively wide bins of 0.5°C width. The average and standard deviation of all the simulated $F_{(T,P)}(\Delta T_g)$ by the individual models falling within each bin are then calculated. This procedure thus provides an estimate of the mean value of $F_{(T,P)}(\Delta T_g)$ and of $\sigma_{IM,(T,P)}(\Delta T_g)$ as a function of the $\Delta T_g$ of each bin. For our ensemble, at least nine individual model simulations are included in each bin. The mean function $F_{(T,P)}(\Delta T_g)$ and intermodel uncertainty $\sigma_{IM,(T,P)}(\Delta T_g)$ resulting from these calculations at each $\Delta T_g$ bin for the Mediterranean and northern Europe cases are given in Tables 2 and 3.

Note that the calculations are carried out only for values of $\Delta T_g$ greater than 0.5°C, because the model spread is much larger than the actual signal for smaller changes. Also, in the MGME simulations analyzed here the value of $\Delta T_g$ for the 20-yr periods considered does not exceed 4°C. Strictly speaking, our approach can thus be considered to be valid only for the GTC range of 0.5°–4°C.
Table 2 first shows that, for temperature, the function $F_T(\Delta T_g)$ is essentially constant for the NEU AMJJAS ($\sim -1.16^\circ C$), MED ONDJFM ($\sim -1.08^\circ C$), and MED AMJJAS ($\sim -1.48^\circ C$) cases, while it shows a decreasing trend with increasing $\Delta T_g$ for NEU ONDJFM. The latter is possibly due to an incremental decrease of snow cover over northern Europe as the global warming increases. This causes a decrease in the snow-albedo feedback process and thus a decrease in the regional temperature sensitivity to global warming. The largest values of $F_T(\Delta T_g)$ occur for the warm-dry season over the Mediterranean and reflect the pronounced sensitivity of summer Mediterranean climate to global warming found in previous studies (Giorgi and Bi 2005; Giorgi 2006).

Concerning the intermodel temperature standard deviation $\sigma_{IM,T}(\Delta T_g)$, we notice two features. First, the values of $\sigma_{IM,T}(\Delta T_g)$ are much smaller than those of $F_T(\Delta T_g)$, which is an indication of the robustness of the simulated temperature change signals. Second, in all regional and seasonal cases we find a decreasing trend of $\sigma_{IM,T}(\Delta T_g)$, with $\Delta T_g$. In other words, relative to the GTC, the models tend to agree more as the change signal increases (while in absolute terms the opposite is true). This is consistent with the finding by Giorgi (2005a) that the scaling approach increases in validity as the magnitude of the forcing and change signal increases.

Turning our attention to precipitation (Table 3), we find roughly constant values of bin-averaged $F_P(\Delta T_g)$ in both seasons over the Mediterranean, both showing decreases ($\sim -3.59^\circ C$ in ONDJFM and $\sim -7.63^\circ C$ in AMJJAS). Over northern Europe we find a decreasing trend of $F_P(\Delta T_g)$ with increasing $\Delta T_g$ in NEU ONDJFM and large variations of values in NEU AMJJAS when, as mentioned above, the change signal by the MGME is not consistent across models. The values of $\sigma_{IM,P}(\Delta T_g)$ for precipitation show a consistent decreasing trend with increasing $\Delta T_g$. For NEU ONDJFM, MED ONDJFM, and MED AMJJAS, the values of $\sigma_{IM,P}(\Delta T_g)$ are comparable to those of $F_P(\Delta T_g)$ for small $\Delta T_g$, indicating that the multimodel signal is not large compared to intermodel noise. For large $\Delta T_g$, however, $\sigma_{IM,P}(\Delta T_g)$ becomes substantially smaller than $F_P(\Delta T_g)$, indicating an increased robustness of the multimodel signal. The exception in Table 3 is the NEU AMJJAS case, for which the intermodel uncertainty is always larger than the multimodel signal.

Fig. 3. Same as Fig. 1, but for global temperature change vs $\Delta T(\text{reg})/\Delta T_g$. 

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As mentioned, the second source of uncertainty we consider here is that due to internal multidecadal variability as measured by the standard deviation \( \sigma_{IV(T,P)}(\Delta Tg) \) (see section 2). This quantity is calculated as follows. Each model simulation falling in each GTC bin is first identified. If, for a given model scenario simulation, more than one realization is available, the anomaly of the change for each realization is calculated as compared to the ensemble average change for that model. This produces a set of anomalies associated with each GTC bin.

### Table 2

Values of the temperature functions \( F_p(\Delta Tg) \), \( \sigma_{IM,T}(\Delta Tg) \), and \( \sigma_{IV,T}(\Delta Tg) \) for different \( \Delta Tg \) bins in the NEU ONDJFM, NEC AMJJAS, MED ONDJFM, and MED ONDJFM cases (see text). Units: °C/°C.

<table>
<thead>
<tr>
<th>( \Delta Tg )</th>
<th>0.5°–1.0°C</th>
<th>1.0°–1.5°C</th>
<th>1.5°–2.0°C</th>
<th>2.0°–2.5°C</th>
<th>2.5°–3.0°C</th>
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<th>3.5°–4.0°C</th>
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<tbody>
<tr>
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<td>1.56</td>
<td>1.54</td>
<td>1.50</td>
<td>1.41</td>
<td>1.40</td>
<td>1.21</td>
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<td>1.15</td>
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<td>1.14</td>
<td>1.15</td>
<td>1.18</td>
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<tr>
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<td>1.08</td>
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<td>( \sigma_{IV,T}(\Delta Tg) )</td>
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**FIG. 4.** Same as Fig. 1, but for global temperature change vs \( \Delta P(\text{reg})/\Delta Tg \).
associated with each simulation for models with multiple realizations of a given scenario. These anomalies are then squared and added including all different model simulations falling within a GTC bin. Finally, $\sigma_{\text{IM},(T,P)}(\Delta T_g)$ is approximated by the root-mean-square of this value. In other words, $\sigma_{\text{IM},(T,P)}(\Delta T_g)$ is defined by the root-mean-square anomaly of the model realizations with respect to the corresponding ensemble average for that model falling within a given GTC bin. Only models for which more than one realization is available are included in the root-mean-square average. In addition, in order to produce values comparable to those of $\sigma_{\text{IM},(T,P)}(\Delta T_g)$, each anomaly is normalized by the respective simulated GTC. It should be emphasized that this procedure gives only a first-order estimate of the internal variability, limited by the availability of a small number of multiple realizations, and evidently gives more weight to the models that completed larger ensembles of realizations.

Tables 2 and 3 summarize the values of $\sigma_{\text{TV},(T,P)}(\Delta T_g)$ for temperature and precipitation change in the northern Europe and Mediterranean cases. We first note that in all cases $\sigma_{\text{TV},(T,P)}(\Delta T_g)$ decreases with $\Delta T_g$. This is essentially because of the normalization by $\Delta T_g$, because the actual values of the root-mean-square multidecadal anomalies do not vary much with increasing $\Delta T_g$. This implies that the multidecadal variability does not change much throughout the twenty-first century MGME simulations. Tables 2 and 3 show that the values of $\sigma_{\text{TV},(T,P)}(\Delta T_g)$ are consistently lower than those of $\sigma_{\text{IM},(T,P)}(\Delta T_g)$, both for temperature and precipitation, and especially for large $\Delta T_g$. This indicates that the uncertainty due to internal variability is lower than the intermodel uncertainty, a result consistent with assessments of previous generations of AOGCM simulations (e.g., Giorgi and Francisco 2000). The contribution of internal variability is however not insignificant, especially for precipitation at relatively small $\Delta T_g$.

Finally, the temperature and precipitation changes along with the related total uncertainty estimates (Eq. 2) for the NEU ONDJFM, NEU AMJJAS, MED ONDJFM, and MED AMJJAS cases are reported as a function of $\Delta T_g$ in Figs. 5 and 6. Also shown are the corresponding least squares fit lines. For temperature change the total uncertainty estimates [as measured by $\sigma_{F,T}(\Delta T_g)$] are much lower than the values of the transfer function $F_T(\Delta T_g)$ in all cases. In three of the cases the function $F_T(\Delta T_g)$ is essentially a constant, while in the NEU ONDJFM case it is a decreasing function of $\Delta T_g$ that is well approximated by a linear fit.

For precipitation (Fig. 6), in all cases, $\sigma_{F,P}(\Delta T_g)$ decreases with increasing $\Delta T_g$, while the value of $F_p(\Delta T_g)$ decreases with $\Delta T_g$ in the northern Europe cases but is essentially constant in the Mediterranean cases. In the NEU AMJJAS case the magnitude of the uncertainty estimate $\sigma_{F,P}(\Delta T_g)$ is actually larger than the magnitude of the transfer function $F_p(\Delta T_g)$ for all values of $\Delta T_g$, while the opposite mostly occurs in the other cases.

We thus see that, especially for precipitation, there is a substantial case-to-case variability in the shape of the function $F_{T,P}(\Delta T_g)$ and in its relative magnitude compared to the corresponding uncertainty estimate $\sigma_{F_{T,P}}(\Delta T_g)$. Figures 5 and 6 also show that a linear fit provides a reasonably good first-order approximation of the $\Delta T_g$ dependence of $F_{T,P}(\Delta T_g)$ and $\sigma_{F_{T,P}}(\Delta T_g)$, at least in the range examined here ($0.5^\circ$–$4^\circ$C). This fit is especially good for temperature, while for precipitation it underestimates the uncertainty at low $\Delta T_g$ and overestimates it at high $\Delta T_g$. In this latter case a higher-
FIG. 5. Values of the mean function $F_T(\Delta T_g)$ (mean) and of $\sigma_{F_T}(\Delta T_g)$ (sigma) at the different $\Delta T_g$ bins for the MGME ensemble and the four cases in Fig. 1. The values are associated to the centers of the bins. Also shown are the corresponding best-fit trend lines.

FIG. 6. Same as Fig. 5, but for $F_P(\Delta T_g)$ (mean) and of $\sigma_{F_P}(\Delta T_g)$ (sigma).
order polynomial fit or an exponential fit might be more accurate.

4. Parameter calculations for other regions

In the previous section we have seen that the transfer function \( F_{T,P}(\Delta Tg) \) and uncertainty estimate \( \sigma_{F_{T,P}}(\Delta Tg) \) can be approximated either by a constant or by a linear function of \( \Delta Tg \). We calculated these values for all the 26 regional wet and dry season cases defined by Giorgi and Bi (2005; the reader is referred thereto for the definitions of regions and wet and dry seasons).

The results are reported in Tables 4 and 5, which show a number of parameters. First, the cases in which a trend in \( F_{T,P}(\Delta Tg) \) or \( \sigma_{F_{T,P}}(\Delta Tg) \) is found to be statistically significant at the 90% confidence level according to a two-tailed \( t \) test are identified. In these cases, \( F_{T,P}(\Delta Tg) \) and \( \sigma_{F_{T,P}}(\Delta Tg) \) are expressed by formulas of the type \( a + (b \Delta Tg) \), and Tables 4 and 5 report the values of \( [a + (b \times 0.5)] \) [i.e., the intercepts of the \( F \) and \( \sigma \) functions at the value \( \Delta Tg = 0.5 \), because Eqs. (1) and (2) are valid only for \( \Delta Tg \) greater than 0.5] and \( b \) (i.e., the slope of the trend line). When a statistically significant trend is not present, \( F_{T,P}(\Delta Tg) \) and \( \sigma_{F_{T,P}}(\Delta Tg) \) are assumed to be constant and equal to their average value across the entire \( \Delta Tg \) range. For these cases this average value is reported in Tables 4 and 5. Finally, for precipitation, cases are highlighted in bold for which the mean value of \( F_P(\Delta Tg) \) across the \( \Delta Tg \) range is greater than the mean value of \( \sigma_{F_P}(\Delta Tg) \), that is, when the signal-to-noise ratio is relatively large. For temperature this is always the case.

Before we analyze the results of Tables 4 and 5, it should be mentioned that the underlying hypothesis of this work (i.e., that the relation of the regional change on the GTC does not depend on the underlying emission scenario) was evaluated for all cases in Tables 4 and 5. As in section 3, this was done by comparing the linear trend lines calculated for the different scenarios separately and for all scenarios compounded together. For temperature we again found that the line slopes varied by less than 10% in the vast majority of cases, showing the solidity of this assumption. For precipitation, the differences were less than 30% for the bold cases in Tables 4 and 5, that is, for the cases in which the signal is greater than the noise. This shows the greater uncertainty present in the use of Eq. (1) for regional precipitation compared to temperature.

Table 4 shows that for temperature \( \sigma_{F,T}(\Delta Tg) \) is always characterized by a significant and negative dependence on \( \Delta Tg \). This indicates that the uncertainty of the predictive regional temperature equation always de-

| Table 4. Values of the temperature parameters (see text): \( F_T(0.5) \); trend in \( F_T(\Delta Tg) \), \( b_T \); mean value of \( F_T(\Delta Tg) \), \( \mu_T \); \( \sigma_{F_T}(0.5) \); and trend in \( \sigma_{F_T}(\Delta Tg) \), \( b_\sigma \). Units: °C/°C² for the function \( F \) and °C/°C² for the trends. Parameter values are reported for the regional cases defined by Giorgi and Bi (2005; see therein for the definition of the regions). May–October (MJJASO), November–April (NDJFMA), February–July (FMAMJJ), August–January (ASONDJ), June–November (JJASON), and December–May (DJFMJ). |
|-----------------|-----------------|-----------------|-----------------|
| \( F_T(0.5) \) | \( b_T \) | \( F_T \) | \( \sigma_{F_T}(0.5) \) | \( b_\sigma \) |
| NEU MJJASO | 1.72 | 0.142 | 0.56 | 0.132 |
| NEU NDJFMA | 1.08 | 0.24 | 0.052 |
| MED ONDJFM | 1.48 | 0.29 | 0.046 |
| MED AMJJAS | 1.39 | 0.43 | 0.068 |
| NEE MJJASO | 1.99 | 0.72 | 0.147 |
| NEE NDJFMA | 1.37 | 0.027 | 0.37 | 0.044 |
| NAS MJJASO | 1.97 | 0.50 | 0.075 |
| NAS NDJFMA | 1.30 | 0.32 | 0.070 |
| CAS MJJASO | 1.64 | 0.038 | 0.34 | 0.063 |
| TIB AMJJAS | 1.43 | 0.28 | 0.047 |
| TIB ONDJFM | 1.54 | 0.34 | 0.067 |
| EAS AMJJAS | 1.11 | 0.40 | 0.24 | 0.034 |
| EAS ONDJFM | 1.27 | 0.36 | 0.082 |
| SAS MJJASO | 1.07 | 0.24 | 0.032 |
| SAS NDJFMA | 1.28 | 0.27 | 0.050 |
| SEA AMJJAS | 0.95 | 0.15 | 0.027 |
| SEA ONDJFM | 0.89 | 0.013 | 0.16 | 0.031 |
| NAU NDJFMA | 1.15 | 0.018 | 0.29 | 0.041 |
| NAU MJJASO | 1.30 | 0.029 | 0.27 | 0.049 |
| SAU MJJASO | 1.05 | 0.037 | 0.26 | 0.051 |
| SAU NDJFMA | 1.05 | 0.013 | 0.26 | 0.045 |
| SAH NDJFMA | 1.29 | 0.24 | 0.055 |
| SAH MJJASO | 1.57 | 0.035 | 0.27 | 0.044 |
| WAF MJJASO | 1.22 | 0.30 | 0.045 |
| WAF NDJFMA | 1.23 | 0.24 | 0.017 |
| EAF MJJASO | 1.21 | 0.26 | 0.018 |
| EAF NDJFMA | 1.20 | 0.22 | 0.027 |
| EAF FMAMJJ | 1.11 | 0.22 | 0.027 |
| EQF ASONDJ | 1.08 | 0.23 | 0.026 |
| SQF NDJFMA | 1.12 | 0.025 | 0.20 | 0.026 |
| SQF MJJASO | 1.28 | 0.28 | 0.039 |
| SAF ONDJFM | 1.17 | 0.015 | 0.26 | 0.039 |
| SAF AMJJAS | 1.23 | 0.008 | 0.27 | 0.041 |
| ALA JJASON | 1.35 | 0.38 | 0.060 |
| ALA DJFMAM | 1.83 | 0.020 | 0.63 | 0.131 |
| GRL JJASON | 1.51 | 0.38 | 0.043 |
| GRL DJFMAM | 1.87 | 0.55 | 0.115 |
| WNA ONDJFM | 1.19 | 0.038 | 0.38 | 0.071 |
| WNA AMJJAS | 1.53 | 0.37 | 0.058 |
| CAN AMJJAS | 1.54 | 0.40 | 0.042 |
| CAN ONDJFM | 1.39 | 0.41 | 0.085 |
| ENA AMJJAS | 1.37 | 0.30 | 0.036 |
| ENA ONDJFM | 1.48 | 0.024 | 0.39 | 0.082 |
| CAM MJJASO | 1.22 | 0.022 | 0.25 | 0.037 |
| CAM NDJFMA | 1.08 | 0.025 | 0.25 | 0.053 |
| AMZ NDJFMA | 1.12 | 0.028 | 0.22 | 0.021 |
| AMZ MJJASO | 1.27 | 0.031 | 0.24 | 0.018 |
| CSA ONDJFM | 1.07 | 0.024 | 0.25 | 0.036 |
| CSA AMJJAS | 1.04 | 0.18 | 0.028 |
| SSA AMJJAS | 0.73 | 0.015 | 0.21 | 0.050 |
| SSA ONDJFM | 0.84 | 0.027 | 0.27 | 0.060 |
Table 5. Values of the precipitation parameters (see text): $F_p(0.5)$; trend in $F_p(\Delta T_g)$, $b_p$; mean value of $F_p(\Delta T_g)$, $F_M$; trend in $\sigma_{F_p}(\Delta T_g)$, $b_\sigma$; and mean value of $\sigma_{F_p}(\Delta T_g)$, $\sigma_M$. Units are %/°C for the function $F$ and %/°C$^2$ for the trends. Parameter values are reported for the regional cases defined by Giorgi and Bi (2005; see therein for the definition of the regions). Bold cases are those in which the mean value of $F$ is greater than the mean value of $\sigma$.

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<th>$F_p(0.5)$</th>
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<th>$F_M$</th>
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<th>$b_\sigma$</th>
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</table>
creases with the magnitude of the signal. Quite a wide range of trend values is found, from \(-0.018^{\circ}\text{C/yr}\) to \(-0.147^{\circ}\text{C/yr}\). In particular, the trend is largest in Northern Hemisphere high-latitude regions [northeastern Europe (NEE), Alaska (ALA), northern Europe (NEU), and Greenland (GRL)] during the cold seasons. This is possibly tied to the progressive reduction of snow and ice cover, which leads to a decrease in intermodel uncertainty. Note also that over these regions the \(\Delta T_g = 0.5\) uncertainty intercept is also the highest, indicating a large uncertainty in the regional temperature sensitivity to global change.

In terms of the temperature transfer function \(F_T(\Delta T_g)\) (Table 4), which has essentially the same meaning as the regional warming amplification factor of Giorgi and Bi (2005), we can see a relatively equal split of regional cases with and without a statistically significant trend. A majority of constant \(F_T(\Delta T_g)\) values is found over the European, Asian, African, and North American regions, while the presence of trends prevails over the Australian, and Central and South American regions. The values of \(F_T(\Delta T_g)\) are generally larger over Northern Hemisphere high-latitude regions in the cold season, indicating a maximum climate response over these regions. Different from the case of \(\sigma_{T_g,T}(\Delta T_g)\), we find trends in \(F_T(\Delta T_g)\) of both positive and negative signs.

In the case of precipitation (Table 5), we find a more varied picture. First of all, only in about 40% of the cases the average value of \(F_T(\Delta T_g)\) is greater than that of \(\sigma_{P,T}(\Delta T_g)\). This indicates that in the majority of cases the uncertainty in the prediction of regional climate change is larger than the compounded signal. This is for a number of reasons: the small magnitude of the precipitation change signal, the large interdecadal variability of regional precipitation, the inconsistency of regional precipitation projections across models, and the need of large ensembles to extract the change signal from the underlying multidecadal and intermodel noise. Among the regions where the magnitude of \(F_T(\Delta T_g)\) is greater than that of \(\sigma_{P,T}(\Delta T_g)\), we find the European regions; Tibet and the north, East, and South Asia regions; eastern equatorial Africa; Alaska; Greenland; and the eastern North America, Central America, and southern South America regions.

Similarly to the case of temperature, the trend in \(\sigma_{P,T}(\Delta T_g)\) is always negative, indicating a relative decrease of uncertainty with increasing \(\Delta T_g\), except for a few cases of constant values (i.e., trends not statistically significant). Also, the trends in \(F_T(\Delta T_g)\) are of both positive and negative signs, and this sign does not appear to be specifically tied to the sign of the precipitation change signal itself. Among the regions with the largest values of \(F_T(\Delta T_g)\), we highlight the northern high-latitude regions (positive values in both wet and dry seasons), the Mediterranean and Central America (large negative values especially in the dry seasons), eastern equatorial Africa (increases in both long and short rainy seasons), and southern South America (large decrease in the dry–cold season).

5. An example of application to the probabilistic prediction of regional climate change

In this section we illustrate how Eqs. (1) and (2) can be applied to produce PDFs of regional climate change from PDFs of GTC. The advantage of this type of application, for example, is that it can be used to produce regional climate PDFs from GTC PDFs generated by large ensembles of simple or intermediate complexity models. This would allow us to better cover the climate change phase space defined by ensembles of models and scenarios and by the internal variability of the climate system (e.g., Giorgi 2005b). In this regard, we base our illustrative application on the GTC PDF shown in Fig. 7. This is a normal PDF distribution close to (although not the same as) the one referred to as “2070” in Fig. 4 of Wigley and Raper (2001), which was obtained using a very large ensemble of simulations with a highly simplified climate system model. Note that the distribution on Fig. 7 fits nicely within the GTC range found in the MGME and used to calculate the transfer functions in this work.

We show two sets of applications. In the first, the transfer function \(F_{T,P}(\Delta T_g)\) is used without consideration of the associated uncertainty, while in the second the uncertainty is accounted for by use of the function \(\sigma_{F_{T,P}}(\Delta T_g)\). For illustrative purposes, these functions...
are applied to estimate the PDFs of temperature and precipitation change in the NEU ONDJFM and MED AMJJAS cases of section 3 using the GTC PDF of Fig. 7.

To apply our method, the GTC range of 0.5°–4°C is first divided into 350 equally spaced bins (i.e., 100 bins per degree). In fact, Fig. 7 shows the PDF based on values calculated at each bin from a normal PDF with mean at 2°C and standard deviation of 0.5°C. In the first type of application, when the uncertainty is not accounted for, the regional change PDF is simply obtained by multiplying the value of the GTC at each bin of the PDF by the transfer function $F_{(T,P)}(\Delta Tg)$ (with the proper unit normalization for temperature and precipitation). This defines a new range of change for the set of 350 bins. The probability density of a given bin is then retained for the “transformed” bins, thereby leading to a transformed PDF.

The results for temperature and precipitation in the NEU ONDJFM and MED AMJJAS cases are shown in Fig. 8. These PDFs can be compared with the “parent” GTC PDF of Fig. 7. For the MED AMJJAS case we first find a shift of the distribution, which retains a shape similar to that of the original GTC PDF. This is because the function $F_{(T,P)}(\Delta Tg)$ is a constant for both temperature and precipitation (see Tables 4 and 5). In the NEU ONDJFM case, however, we notice not only a shift, but also a deformation of the PDF, which becomes slightly asymmetric. This is because the function $F_{(T,P)}(\Delta Tg)$ has a decreasing trend with increasing GTC (see Tables 4 and 5). In addition, the transformed PDFs for the regional temperature changes are somewhat broader compared to the original GTC PDF, as evidenced by the fact that the standard deviation increases from 0.5°C in the GTC PDF to 0.61° and 0.73°C for the MED AMJJAS and NEU ONDJFM cases, respectively.

To include the effect of the uncertainty defined by the function $\sigma_{F_{(T,P)}}(\Delta Tg)$ we proceed as follows. First, we assume that the uncertainty at any given bin can be described by a normal PDF centered on the bin, having a standard deviation equal to $\sigma_{F_{(T,P)}}(\Delta Tg)$ and a median probability density value equal to the probability density of the GTC PDF at that bin. We then apply the transfer function $F_{(T,P)}(\Delta Tg)$ to the GTC PDF bin range in order to generate a new set of “transformed” bins for the regional changes. At each of the transformed bins we add the contribution to the probability...
density deriving from each PDF of all individual transformed bins. Finally, the resulting distribution is normalized in order to preserve the integral of the original GTC PDF.

The results from this procedure are shown in Fig. 9 and can be compared with the PDFs of Fig. 8 and the parent GTC PDF of Fig. 7. Note in Fig. 9 that the PDFs are defined only within the range of GTC used to derive the transfer and uncertainty functions; however, they could be extrapolated to wider GTC ranges with proper extrapolation of the functions $F(T,P)(\Delta T_g)$ and $\sigma_{F(T,P)}(\Delta T_g)$. An overall intercomparison of the PDFs in Figs. 8 and 9 shows that the addition of the uncertainty does not shift much the distributions, but affects the shape of the PDFs. In general, as can be expected, the PDFs become wider when the uncertainty is accounted for (for temperature the standard deviations increase from 0.5°C in the GTC PDF to 0.88°C and 1.13°C in the MED AMJAS and NEU ONDJFM cases, respectively). The smallest effect of the uncertainty is found for the temperature change in the MED AMJAS case, when the value of $\sigma_{F(T)}(\Delta T_g)$ is small (see Table 4). The largest effects are found in the case of the precipitation change PDFs, where in particular the tails of the distributions are modified. The transformed regional precipitation change PDFs cannot be considered Gaussian any more and are asymmetric with respect to the center of the distribution, with the large change portion of the distribution becoming effectively a straight line.

6. Summary considerations and discussion

In this paper simple equations are developed for regional climate change prediction and related uncertainties, where both these equations are expressed as a function of the GTC. The key underlying assumption in the use of Eqs. (1) and (2) is the remarkable scaling property that some surface climate variables show with respect to the global radiative forcing and GTC response. These properties hold especially well for temperature, giving Eqs. (1) and (2) a good level of robustness. For precipitation, the assumption holds, although in a less robust way, only for the cases in which the change signal is greater than the underlying uncertainty. It should be emphasized that, compared to the standard scaling approach, the method described here adds the estimate of the uncertainty due to intermodel and internal variability.

The recently developed MGME dataset (online at...
http://www-pcmdi.llnl.gov) is used to derive the parameters of our equations. The methodology and the functioning of our equations are illustrated using temperature and precipitation change data over two subcontinental scale regions, northern Europe and the Mediterranean (as defined by Giorgi and Bi 2005). Parameter values are also presented, however, for temperature and precipitation change over 26 regions (from Giorgi and Bi 2005), encompassing all land areas of the globe (except for Antarctica). Finally, examples are shown of the application of Eqs. (1) and (2) to the generation of PDFs of regional climate change based on GTC PDFs.

This last application makes Eqs. (1) and (2) especially useful, because it allows us to estimate probabilities of regional climate change from the output of simple or intermediate complexity models. These models can in fact be run for very large ensembles encompassing much of the climate change parameter space. The approach presented in this paper thus provides a tool for probabilistic regional climate change prediction to complement existing methodologies (Räisänen and Palmer 2001; Giorgi and Mearns 2002, 2003; Stott and Kettleborough 2002; Forest et al. 2002; Tebaldi et al. 2005; Harris et al. 2006; Räisänen and Ruokolainen 2006; Stott et al. 2006).

Another attractive characteristic of our approach is that it provides a first-order estimate of regional climate change disentangling this estimate from the issue of scenarios and emission pathways, which has drawn much debate recently (e.g., Holtsmark and Alfsen 2005). Rather, the regional change estimates are only based on the GTC. Therefore, our equations would, for example, allow us to estimate the first-order regional response associated with given target GTC and GHG stabilization levels along with the associated uncertainty.

The limit of the approach evidently resides in the magnitude of the uncertainty, which in our case depends on the contributions of intermodel and internal variability. This uncertainty is a measure not only of the signal-to-noise ratio, but also of the validity of the basic underlying scaling assumption. We have seen that for temperature the uncertainty [as measured by the function \( \sigma_{ET}(\Delta T_g) \)] is much smaller than the signal [as measured by the function \( F_I(\Delta T_g) \)] for all cases, so that the signals deriving from the use of Eqs. (1) and (2) can be considered robust. Conversely, for precipitation this is the case only for a much more limited number of cases, in which the precipitation change signal is especially large.

This method can be extended in various directions, first of all by considering the application to different variables (e.g., sea level pressure or circulation indicators) and/or higher-order statistics (e.g., variability and extremes). It would also be important to verify the scale limit for which the approach is valid. This paper focuses on the subcontinental scale, primarily because the resolution of the MGME models is highly variable, with some models still being run at rather coarse horizontal resolutions (4°–5°). It has been shown, however, that the surface climate change signal, in particular precipitation, shows substantial finescale structure in response to local forcings (e.g., topography; Gao et al. 2006), so that the scaling hypothesis underlying our approach needs to be verified at fine scales.

Another important issue concerns the effects of regional–local (aerosols, land-use change) versus global (GHG concentration) forcings. It can be expected that these different forcings might have different regional effects, which would in turn affect the scalability assumption underlying the validity of Eq. (1). The simulations analyzed here included both types of forcings (GHG and aerosol), which varied across different scenarios. Remarkably enough, although the aerosol forcings are different in the different scenarios (Nakicenovic et al. 2000), the scalability assumption still seems to hold, which is suggestive of a dominant contribution of the GHG forcing for the experiments employed. These experiments however did not include all aerosols, so that aerosol effects might indeed be underestimated. In addition, they did not account for the effects of land-use change, which can also be especially important at the regional scale (Feddema et al. 2005). Therefore, the issue of regional versus global forcing needs to be carefully considered with more comprehensive model experiments.

The method developed in this paper hinges upon the availability of a sufficiently large number of intercomparable AOGCM simulations to develop meaningful calculations of the different parameters appearing in Eqs. (1) and (2), in particular the uncertainty functions. In this regard, the author would like to commend the MGME effort and recommends that such efforts be continued and further extended in the future to produce large enough ensembles of climate change simulations to improve our understanding and predictive capability of regional climate change.

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