Changes and inter-model spread in 21st century scenarios for temperature and precipitation extremes as seen with the climate change index (CCI)

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Abstract

The amplitude and inter-model spread (IMS) of late 21st century changes in temperature and precipitation extremes in 21 Coupled Model Intercomparison Project 3 models are analyzed using the recently introduced climate change index (CCI) and its components. Strong changes in extremes are found which are similar to those found using older data. Large IMS is found mostly in regions where the multi-model mean CCI values are large (tropics land, polar regions) or small (El Niño Southern Oscillation (ENSO) region, North Atlantic Ocean). The two regions with large IMS in the tropics (ENSO region, Amazon basin) are mainly related to different model changes in precipitation extremes. In the polar regions the large IMS is linked to the IMS in both temperature and precipitation changes. Although the multi-model mean CCI values are average and the IMS is smallest in the subtropics, considerable change but also IMS is found as regards the changes of extremely dry events in this region. In this and other cases, a detailed analysis of the CCI components is important for getting a more complete picture of the changes and IMS of extreme temperature and precipitation events.

Keywords: climate change, extremes, temperature, precipitation, inter-model scatter, CCI, SRES A1B, CMIP3, scenarios, regional, multi-model

1. Introduction

Several studies have shown that there is a need for reliable and well-synthesized (simple) information about climate change and its potential impacts on many aspects of life on Earth [1, 2]. To address this need [2] defined a simple and transparent climate change index (CCI) which quantifies changes in rather extreme (‘1 in 20 years’) temperature and precipitation events on a seasonal and annual timescale. They applied it to a small subsample of Intergovernmental Panel on Climate Change (IPCC) third assessment report (TAR) models (ECHAM5, HadCM3 and CGCM2) and compared their results with other aggregated indices used in the literature, e.g. [3]. Since they focused on method development and because of the small number of models considered, they did not address the differences from model to model, i.e. inter-model spread (IMS). In this study, we use an extended version of the [2] CCI (section 2.2), apply it to Coupled Model Intercomparison Project 3 (CMIP3) models over both land and sea, compare with earlier results and quantify the amount of IMS in terms of changes in ‘1 in 20 years’ events (section 3.1). In section 3.2 the CCI components (hot/dry/wet) are analyzed separately.
(i) using global maps in order to quantify their importance in determining the CCI and (ii) for regions with large or small IMS in CCI. In contrast to many studies which discuss only consistent patterns of change, (e.g. [4] and [5]) we also focus on regions with large IMS and thus where model improvements are especially beneficial.

2. Data and methods

2.1. Data

Monthly data of the SRES runs prepared in the context of the IPCC forth assessment report (AR4) now known as CMIP3 data set are analyzed (see http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php for details). The variables used are tas (2m temperature) and pr (precipitation). The time periods considered are 1971–2000 (control period) and 2070–2099 (scenario period). For the control period, we use the climate of the 20th century (20C3M) runs which (depending on the model) incorporate various natural and anthropogenic forcings including changes of greenhouse gases, ozone and aerosol distributions (cf [6], table 10.1). For the scenario period the A1B mid-range scenario is considered. The first member run of the following 21 models is used (for details on models see table 8.1 in [7], letters as in figures): (a) CGCM3.1(T47), (b) CGCM3.1(T63), (c) CNRM-CM3, (d) CSIRO-MK3.0, (e) GFDL-CM2.0, (f) GFDL-CM2.1, (g) GISS-AOM, (h) GISS-EH, (i) GISS-ER, (j) FGOALS-g1.0, (k) INM-CM3.0, (l) IPSL-CM4, (m) MIROC3.2(hires), (n) MIROC3.2(medres), (o) ECHO-G, (p) ECHAM5/ MPI-OM, (q) MRI-CGCM2.3.2, (r) NCAR-CCSM3, (s) NCAR-PCM, (t) UKMO-HadCM3. (u) UKMO-HadGEM1. All model fields have been interpolated bilinearly to 2.5° × 2.5° and all computations were done globally for every grid point.

2.2. Methods

All indicators are calculated according to [2] who identify the ‘1 in 20 years’ most extreme event in the reference period. Then the number of additional occurrences I of such an event within the scenario period is computed. In contrast to [2] where a parametric fit is used to determine the number of additional ‘1 in 20 years’ events we use the non-parametric quantile function type 8 (cf [8]) in the statistics package R (http://r-project.org). The two methods give very similar results (not shown). For the computation of the CCI we use a slightly adapted version of the CCI which includes also spring (MAM) and autumn (SON). The new terms are underlined:

\[
CCI = (I_{\text{HOT} \text{MAM}} + I_{\text{DRY} \text{MAM}} + I_{\text{WET} \text{MAM}} + 1/2I_{\text{HOT} \text{SON}} + 1/2I_{\text{DRY} \text{SON}} + 1/2I_{\text{WET} \text{SON}})/(6).
\]

Several points have to be mentioned here. (i) The temperature (I_{\text{HOT}}) and precipitation (I_{\text{DRY}} and I_{\text{WET}}) components are weighted the same in the CCI. Since the relative changes in extreme temperature tend to be larger than those in extreme precipitation, the changes in temperature extremes influence the CCI more than the changes in precipitation extremes. To get a more complete picture of the changes it is therefore important to also analyze the components I_{\text{HOT}}, I_{\text{DRY}} and I_{\text{WET}} separately (cf section 3.2), (ii) Scherrer [19] found only small differences in multi-model mean temperature changes and their inter-model spread when the models are weighted according to their past performance. Therefore, all models are assigned the same weight in the CCI computation. An exception is FGOALS-g1.0 which shows extreme temperature biases in mid- and high-latitudes (cf [9]) and is excluded in this case and for most analyses below. (iii) The CCI does not include potentially very important but highly uncertain processes such as changes in sea level or in the models hardly represented phenomena such as hurricanes which are of particular importance for the often densely populated coastal regions. As a result the CCI might be more representative for non-coastal regions and cannot be used to judge impacts in flat coastal regions or to e.g. assess changes in wind storm damages.

Below we discuss multi-model mean (MMM) and single-model results, IMS expressed as inter-model standard deviation (sd_{CCI}) and results from single-variable fields (the number of additional extreme hot, dry and wet seasons).

3. Results

3.1. Mean and inter-model spread in CCI

Figure 1 shows the map of CMIP3 CCI{MMM} for all grid points and the 2070–2099 period (reference period is 1971–2000). In general the index is highly similar to the land-only CCI produced by [2] using IPCC TAR data of three models only (ECHAM5, HadCM3 and CGCM2, cf their figure 2(a)). Large values are found for the Northern Hemisphere (NH) polar region, the Southern Atlantic and Indian Ocean (incl. the south-west coast off Australia), Tibet, Central America, the Caribbean Islands, north-western South America, Central Africa, the Malay Archipelago and the Mediterranean region. Relatively small values are found for the north Atlantic deep water formation region, Eastern Europe, south-eastern South America, America, the central tropical Pacific Ocean (ENSO region) and central and southern North America. The CMIP3 CCI{MMM} values are smaller than the TAR values in the Amazon basin, south-western Africa and to some degree also in Central Africa (cf figure 2 in [2]). In contrast, CMIP3 CCI{MMM} values are larger for the Northern Hemisphere polar region and for the Indian subcontinent.

The fact that the CMIP3 results are based on 21 different models allows to quantify the IMS in more detail. The regions with small IMS (sd_{CCI} < 1, stippled regions in figure 1) are mainly found in the subtopics where the CCI{MMM} values are small or intermediate (especially over sea, e.g. the Indian, Atlantic and western Pacific Ocean with the global IMS minimum sd_{CCI} of 0.37). The smallest IMS over land is found for south-eastern parts of Africa (sd_{CCI} ∼ 0.5), the desert regions in northern Africa as well as Saudi-Arabia and Australia (sd_{CCI} ∼ 0.75). The large IMS regions (sd_{CCI} > 2, hatched in figure 1) are predominantly those
where the CClMM values over sea are very large (NH polar region, southern Oceans) or small (northern Atlantic deep water formation region with the global IMS maximum sdCCI = 4.69, central tropical Pacific Ocean (ENSO) regions, Southern Hemisphere polar region). Over land, especially large IMS values are found for the Amazon basin and the polar regions. All these regions are well known as ‘problem’ regions where some major biases exist and where models still struggle with a good representation of certain physical phenomena (e.g. ENSO, tropical convection and precipitation, atmospheric waves, oceanic deep water formation, sea ice, snow, clouds, cf e.g. [7]).

Another fact is that the IMS is moderate (1 < sdCCI < 2) for the small CCI regions over land (North America, south-east South America, Eastern Europe, Australia). Hence, there is more spread in the changes over sea than over land for regions where the CCI is supposedly small.

The IMS computation only includes one run from each model. However, it is interesting to see how different runs of one model or models of the same institution compare with the other models. We find that the grid point values and global maps of the members of a single model are highly similar (e.g. for NCAR-CCSM3, not shown) confirming that the way the members are perturbed initially has almost no influence on the changes in extremes in the late 21st century. Although the grid point values of similar models, e.g. CGCM3.1(T47) and CGCM3.1(T63), GFDL-CM2.0 and GFDL-CM2.1, GIS-EH and GISS-ER, MIROC3.2(hires) and MIROC3.2(medres) can be somewhat different, the global grid point maps are quite similar too (not shown). This seems a plausible explanation since they share a certain amount of similar or even the same code for some modules. Comparing patterns between model ‘families’ (i.e. different institutions) on the other hand reveals substantial differences. Especially large are the differences in the tropics where some models show large values for CCI in the ENSO regions (CGCM3.1, the GISS and MIROC models, MRI-CGCM2.3.2), whereas others show relatively small values (CNRM-CM3, CSIRO-MK3.0, the GFDL models, FGOALS-g1.0, ECHO-G, NCAR-PCM and CCSM).

3.2. Analysis of the CCI components

For climate impact and application purposes it is crucial to identify the CCI components (variable, season and models) which are responsible for the small or large IMS in the CCI. Moreover, the dry and wet components are averaged together in the CCI (cf equation (1)). Since precipitation processes are highly non-linear it seems reasonable to investigate the wet/dry components separately. Therefore, section 3.2.1 discusses grid point based global maps of the components and their spread. In section 3.2.2 the focus is on the CCI components for regions on land and sea where the CCI IMS is especially large or small.

3.2.1. Global maps for temperature and precipitation components

Figure 2 shows the grid point based MMM changes in ‘1 in 20 years’ temperature (I_HOT, top) and precipitation components (I_WET and I_DRY, middle and bottom) for DJF (left) and JJA (right). In DJF the MMM of I_HOT is very large with more than 14 additional events (red colors) for almost all regions except some parts of the northern Atlantic Ocean, North America, Central Asia, the ENSO region and the southern Oceans in DJF. For JJA, I_HOT is particularly large for the SH westerlies region. In DJF, the MMM of I_WET is very large with more than 14 additional events (red colors) for almost all regions except some parts of the northern Atlantic Ocean, North America, Central Asia, the ENSO region and the southern Oceans in DJF. For JJA, the MMM changes in wet extremes are large (I_WET > 7 additional events) for the NH polar region, parts of central Asia (incl. Tibet) and in the SH westerlies region. In JJA, I_WET is particularly large for the SH westerlies region. In
DJF and JJA $I_{\text{WET}}$ is considerable also for the tropics (land and sea).

The increase in extremely dry DJF and JJA is somewhat smaller in amplitude and confined to the subtropics and adjacent tropical and mid-latitude regions (e.g. JJA in western Europe). In general, the patterns found are very similar to the patterns of the changes in the means for these seasons (cf [6], figure 10.9). The changes in extremes are basically caused by changes in the mean and not changes in standard deviation as also found by [2] and several other authors (e.g. [10–12]).

The stippled areas in figure 2 show where the inter-model standard deviations are larger than 3 ‘1 in 20 years’ units. Although this limit is arbitrary, tests showed that it allows to identify where the CCI components show considerable inter-model spread. For the temperature component $I_{\text{HOT}}$ the large spread is often found in regions with relatively small changes (yellow/orange regions in figure 2). For large parts of the tropics and subtropics with very high CCI values the spread is small. This is partly caused by the fact that a lot of models reach the upper limit of 19 additional extreme events and the spread thus gets small by definition. For the precipitation components $I_{\text{WET}}$ and $I_{\text{DRY}}$, large values of $I_{\text{WET}} (I_{\text{DRY}})$ are also regions with large inter-model spread. Note that this does not mean that the MMM changes are not significant. In fact there are a lot of regions where the MMM change is larger than 1 or 2 inter-model standard deviations, but the ‘amplitude’ of the change still varies a lot from model to model.

The large spread regions identified for the CCI components discussed above (dotted in figure 2) are useful to disentangle which components cause large spreads in CCI (hatched regions in figure 1). For $I_{\text{HOT}}$ and $I_{\text{WET}}$ the DJF and JJA large spread regions agree well with large or at least average value spread regions identified for CCI in figure 1. This shows that the spread created by these components is well represented by the spread in CCI. The situation is different for $I_{\text{DRY}}$, where both the DJF and JJA large spread regions are located in low or average CCI spread regions and thus an example for a component spread which is not optimally represented by the CCI spread. In order to get a better feeling for the model differences in $I_{\text{DRY}}$, figure 3 is
Figure 3. Number of additional extremely dry 2070–2099 JJA for all 21 models investigated.
3.2.2. Regions with small/large IMS in CCI. In this subsection we present the CCI components for some core climatological regions on land and sea where the CCI IMS is large (sd_{CCI} = 2–3, the ENSO 3.4 region and Amazon basin) or small (sd_{CCI} ~ 0.5, the western subtropical Pacific Ocean and south-east Africa) plus for the NH polar region (cf figure 4).

For the ENSO 3.4 region [17], a region with large IMS over sea (sd_{CCI} ~ 2–3), the spread is caused by both the uncertainties in the changes in extreme temperatures and extreme precipitation, although the spread in precipitation is dominant (figure 4 upper left panel). There is a tendency towards wetter extremes in all seasons, but the amplitude is highly uncertain. The most extreme models are the MIROC3.2 (hires) model which shows between 8 and 13 additional extremely wet seasonal values in all seasons and the GISS-ER model which suggests more dry extremes (esp. in MAM). For the Amazon basin region (sd_{CCI} ~ 2–3), a good example of a region with large IMS over land, the main source of CCI spread is precipitation which is ‘all over the place’. On the dry side are the Hadley Centre models HadGEM1 and especially HadCM3 with up to 16 additional extremely dry seasons (esp. for summer/autumn and the whole year). GISS-ER, GISS-EH and IPSL-CM4 on the other hand show 7–13 additional extremely wet seasonal values in all seasons and the GISS-ER model which suggests more dry extremes (esp. in MAM).

For the Amazon basin region (sd_{CCI} ~ 2–3), a good example of a region with large IMS over land, the main source of CCI spread is precipitation which is ‘all over the place’. On the dry side are the Hadley Centre models HadGEM1 and especially HadCM3 with up to 16 additional extremely dry seasons (esp. for summer/autumn and the whole year). GISS-ER, GISS-EH and IPSL-CM4 on the other hand show 7–13 additional extremely wet seasons. Studies show that the precipitation changes in the Amazon basin region seem connected with ENSO and therefore possibly influenced by the also highly uncertain modeled changes in the ENSO region, e.g. [10]. For winter and spring the GFDL-CM2.1 model shows much smaller changes in hot extremes than the other models (cf figure 4).
Considerable differences between models. This stresses that in subtropical and mid-latitude extreme summer dryness shows intermediate values. Nevertheless, the amount of the changes is found for many parts of the subtropics where the CCI has values for temperature and precipitation extremes. The smallest IMS (esp. the NH) the large IMS is caused by both spread in changes which range from somewhat dryer to much wetter for (i) and mainly related to different changes in precipitation extremes the tropics (i) the ENSO region and (ii) the Amazon basin are also the regions where CCI values are large (tropics land, NH changes and not different signs since all models tend towards more wet extremes.

The right panels of figure 4 show examples of two regions where the CCI IMS is small (sdCCI \sim 0.5, the western subtropical Pacific Ocean and south-east Africa). Expectedly the IMS for the individual CCI components is much smaller than for those in the large IMS cases. The main spread still comes from the uncertainty in extreme precipitation changes whereas the spread in the extreme temperature changes is very small since they are close to maximal.

4. Conclusions

We applied an updated version of the [2] climate change index (CCI) and its components to the CMIP3 A1B climate projections to assess the magnitude and the underlying model-to-model differences in the changes of temperature and precipitation extremes at the end of the 21st century. The results show that with the exception of the changes in dry extremes, the multi-model mean CCI and the CCI inter-model spread give a good overview where large changes and model uncertainties in extreme temperature and precipitation related extremes can be expected. The CCI values found compare well with those reported in [2] for TAR data. High CCI values are found for the NH polar region, the Southern Atlantic and Indian Ocean, Tibet, Central America, the Caribbean Islands, north-eastern South America, Central Africa, the Malay Archipelago and the Mediterranean region. Relatively small values are found for the north Atlantic deep water formation region, Eastern Europe, south-east South America, Australia, the central tropical Pacific Ocean and the central and southern USA. Note that small does not at all mean insignificant but only smaller compared to other regions.

Although the CMIP3 model simulations show increasingly consistent regional patterns in mean and extreme changes for many regions (cf [6, 18]), the CCI inter-model standard deviation varies between 0.37 and 4.69 (a factor 12.8) indicating considerable differences in the changes of extremes especially for tropical and high-latitude ocean regions (e.g. all regions south of 50\degree S). The regions with large IMS are mostly also the regions where CCI values are large (tropics land, NH polar region) or small (ENSO region, North Atlantic deep water formation region). The two regions with large IMS in the tropics (i) the ENSO region and (ii) the Amazon basin are mainly related to different changes in precipitation extremes which range from somewhat dryer to much wetter for (i) and extreme drying to much wetter in (ii). In the polar region (esp. the NH) the large IMS is caused by both spread in changes of temperature and precipitation extremes. The smallest IMS is found for many parts of the subtropics where the CCI has intermediate values. Nevertheless, the amount of the changes in subtropical and mid-latitude extreme summer dryness shows considerable differences between models. This stresses that for extreme dryness the CCI spread is not representative and an analysis of the original IDR and its inter-model spread is indispensable to identify problem regions for that particular variable.

To judge whether the inter-model spread could be reduced, model weighting with respect to their performance in past and present day climate is sometimes suggested. First attempts using temperature performance only [19] show only small differences in temperature changes and their inter-model spread when the models are weighted. However, the verification of climate models is tricky and more research is needed to determine whether inter-model spread can be reduced based on model weighting using verification measures. It is clear that in the long term, inter-model spread preferably should be reduced by model improvements, i.e. implementing more accurate physical formulations.

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