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Perceptible changes in regional precipitation in a future climate

Irina Mahlstein,[1] Robert W. Portmann,[1] John S. Daniel,[1] Susan Solomon,[2,3] and Reto Knutti[4]

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[1] Evidence is strong that the changes observed in the Earth's globally averaged temperature over the past half-century are caused to a large degree by human activities. Efforts to document accompanying precipitation changes in observations have met with limited success, and have been primarily focussed on large-scale regions in order to reduce the relative impact of the natural variability of precipitation as compared to any potential forced change. Studies have not been able to identify statistically significant changes in observed precipitation on small spatial scales. General circulation climate models offer the possibility to extend the analysis of precipitation changes into the future, to determine when simulated changes may emerge from the simulated variability locally as well as regionally. Here we estimate the global temperature increase needed for the precipitation "signal" to emerge from the "noise" of interannual variability within various climatic regions during their wet season. The climatic regions are defined based on cluster analysis. The dry season is not included due to poor model performance as compared to measurements during the observational period. We find that at least a 1.4°C warmer climate compared with the early 20th century is needed for precipitation changes to become statistically significant in any of the analysed climate regions. By the end of this century, it is likely that many land regions will experience statistically significant mean precipitation changes during wet season relative to the early 20th century based on an A1B scenario. **Citation:** Mahlstein, I., R. W. Portmann, J. S. Daniel, S. Solomon, and R. Knutti (2012), Perceptible changes in regional precipitation in a future climate, *Geophys. Res. Lett.*, *39*, L05701, doi:10.1029/2011GL050738.

1. Introduction

[2] The Earth's climate system has warmed over the past half-century. The IPCC Working Group I Fourth Assessment Report states with very high confidence that humans have dominated this warming by emitting greenhouse gases into the atmosphere [*Intergovernmental Panel on Climate Change*, 2007]. This finding is based on a number of studies showing that anthropogenic climate change is attributable to human activities [*International Ad Hoc Detection and Attribution Group* (*IDAG*), 2005; *Min et al.*, 2008; *Stott et al.*, 2000]. Different approaches exist to distinguish anthropogenic forcing from natural forcing such as optimal fingerprinting [*IDAG*, 2005] or Bayesian methods [*Schnur and Hasselmann*, 2005]. The anthropogenic impact on surface temperature [*Gillett et al.*, 2008; *Stott*, 2003] and on other climate variables [*Gillett et al.*, 2003; *Santer et al.*, 2003; *Zhang et al.*, 2007] is also detected on sub-global scales. However, on a regional scale few studies exist that show changes in precipitation. *Zhang et al.* [2007] analysed latitudinal bands and were able to detect changes in precipitation and attribute it to human influence. *Min et al.* [2008] find an influence in precipitation over high latitude land areas north of 55°N from anthropogenic greenhouse gases and sulphate aerosols during the second half of the 20th century. Changes in seasonal precipitation across different observational datasets are also detected within latitude bands and compare favourably to model results [*Noake et al.*, 2012]. In these studies, the area over which data is aggregated extends over large regions. A few studies have addressed when a climate signal can be detected [*Deser et al.*, 2012; *Diffenbaugh and Scherer*, 2011; *Giorgi and Bi*, 2009; *Hawkins and Sutton*, 2012; *Joshi et al.*, 2011; *Mahlstein et al.*, 2011], but *Giorgi and Bi* [2009] is the only one that considered past precipitation. However, they only analysed 14 hot spots whereas this study considers all regions over land except Antarctica. *Deser et al.* [2012] only considered future changes.

[3] Regional detection of precipitation changes is described by few studies [*Perreault et al.*, 1999; *Tomozeiu et al.*, 2000]. The climate in particular locations is highly variable, raising the question of where and when local changes could also become perceptible enough to be obvious to people in the form of local drying or wettening that exceeds interannual variability. However, a comprehensive global overview of all climatic regions that describes when precipitation changes become perceptible (i.e., a distribution that is notably different to interannual variations experienced in past climate) has not been performed. In this paper we conduct a regional study of changes in precipitation and estimate at what global temperature increase the signal of change emerges from natural climate variability averaged over the wet season (hereafter the mean precipitation over the wet season is referred to as WSP). This is done by scaling the global temperature changes with changes in precipitation [*Allen and Ingram*, 2002]. We note that the changes averaged over the wet season may not be the aspect of precipitation that is first detectable (e.g., heavy precipitation events may be detected earlier) nor does it take into account changes in annual precipitation and other quantities. The wet season is chosen because although the models generally underestimate precipitation trends [*Noake et al.*, 2012; *Zhang et al.*, 2007], they reproduce sufficiently realistic precipitation regimes and changes in the wet season. Most

[1]Earth System Research Laboratory, NOAA, Boulder, Colorado, USA.
[2]Department of Atmospheric and Oceanic Sciences, University of Colorado at Boulder, Boulder, Colorado, USA.
[3]Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA.
[4]Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland.

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of the largest discrepancies between models and data are in the dry season (see auxiliary material).[1]

2. Data and Method

[4] We use the SRES A1B scenario runs from 21 atmosphere ocean general circulation models (AOGCM), which are available from the World Climate Research Program (WCRP) Coupled Model Intercomparison Project Phase 3 (CMIP3) [*Meehl et al.*, 2007]. All model output is regridded to a common T42 grid and, if several runs are available, the first run is always used. Because models demonstrate varying degrees of quality of performance in different geographic regions [*Schaller et al.*, 2011], no pre-selection of models was applied, and all models were included in the analysis. The wet season is defined as the three wettest consecutive months of the year during the 1900–1929 period.

[5] Similar to the perception of temperature changes [*Mahlstein et al.*, 2011], the ability to determine when the signal emerges from the noise for precipitation changes is dependent on the size of the signal compared with the variability. Thus, the climate variability must be carefully considered to determine when any precipitation changes become statistically significant. A measure of climate variability of precipitation during the wet season can be defined as the standard deviation of the time series D:

$$\mathrm{D(t)} = \mathrm{PR_w(t+1)} - \mathrm{PR_w(t)}, \tag{1}$$

where $\mathrm{PR_w}$ denotes the precipitation during the wet season in the year t [*Jenkins and Watts*, 1968]. This method removes any slowly varying component without assuming any particular form. To facilitate the interpretation, all results are shown as percentage values relative to the 30-yr base period from 1900–1929, which is the first 30-yr period available in the observations. Note that the spatial pattern of variability is only used to compare observations and models, and that the exact definition of variability used in such comparisons does not affect our conclusions (see auxiliary material for details).

[6] The time of emergence of WSP changes is identified for each model when the Kolmogorov-Smirnov test rejects with 5% significance that two samples of 30-yr time periods are drawn from the same distribution. This is a non-parametric test that allows for such an evaluation when the distribution statistics of the precipitation data are not known. This test is sensitive to changes in the mean, but less to changes in the tails. The base period (1900–1929) is compared to sequential periods defined by a moving time window starting at 1910–1939, progressing in 10-yr time steps. The time stepping is continued until the signal emerges as a significant change, or in case of no emergence, until the end of the A1B scenario in 2070–2099. For more details about the statistical testing see *Mahlstein et al.* [2011]. However, in contrast to that study, the test here is applied to regions in addition to grid cells to reduce the effects of the much higher spatial variability of precipitation as compared to temperature (see below). To increase the robustness of the results, a minimum percentage of models must agree on the sign of change (drier or wetter) and show a significant change before 2100 during the wet season. The time of emergence of a significant WSP change is taken as the time when a given percentage of all models demonstrate a significant change. In this study, results for the 66% and 90% quantiles of the temperature increase needed among the models are shown, which corresponds to likely and very likely in IPCC terminology (see auxiliary material for details). The last year of the 30-yr time period in which significance arises is taken as the year of emergence, which can also be converted to a temperature level above 1900–1929 mean global temperature for each model. The temperature of emergence is then the 66% and 90% quantiles, respectively, of the models. Providing a temperature level instead of a year as the time of emergence has the advantage of making the results nearly scenario independent.

3. Future Perceptible Changes in Precipitation Changes During Wet Season Based on Climate Models

[7] We first compare the model results with observed wet season average precipitation and variability. The observational data used are taken from the Hulme data set (1900–1998), which is based on gauge data on land [*Hulme*, 1992]. Note that the model data are a multi model mean and therefore are much smoother compared to the single observational data set. The models do reasonably well in reproducing the observed WSP measures defined below, as is shown in Figure 1. In general, they slightly underestimate the variability (Figures 1a and 1d), and the signal, defined as the difference in mean precipitation during the wet seasons of 1970–1998 and 1900–1929, is also underestimated in large areas over land (Figures 1b and 1e). Therefore, the signal to variability ratio is too low in the models compared with the observations (Figures 1c and 1f). Figure 1 suggests that the time of emergence may happen earlier in the real world than presented in this study but that the patterns of changes are represented correctly in the models. Nonetheless, the emergence of the signal of local precipitation changes during the wet season is not expected very soon, mainly because of the large year-to-year variability. However, regional analysis significantly improves the emergence of the signal as illustrated in Figures 3a, 3b, 3d, and 3e. Figures 3a and 3d show the global temperature increase relative to 1900–1929 needed for the emergence of the signal on a grid scale level whereas the middle panel shows the global temperature increase needed for WSP to change significantly in a specific region. For reference the regions are shown in Figure 2. The regions used were defined by *Mahlstein and Knutti* [2010] for precipitation and are based on a cluster analysis that considers current climatology of precipitation as well as future changes. On the uninhabited continent of Antarctica, data are limited to a very few sites and so this region is not included here. The wettening of the northern North American Continent and the eastern-most part of Africa are the only two areas where at least 90% of the models agree on significant changes at the grid-scale level (Figure 3e). However, for large areas over land it is likely (66%) that a significant change will occur if the Earth continues to warm. The drying of the Mediterranean region is a robust finding, and it is also significant on the grid scale level (Figure 3a) as reported previously using a somewhat different approach [*Giorgi and Lionello*, 2008]. Furthermore,

[1] Auxiliary materials are available in the HTML. doi:10.1029/2011GL050738.

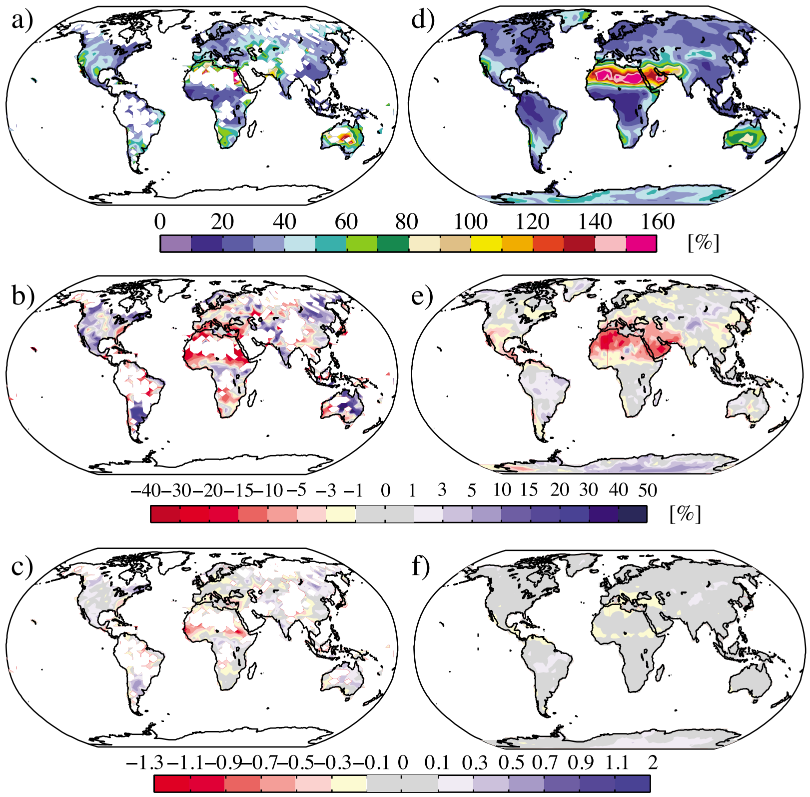

Figure 1. Comparison between (left) observations and (right) multi model mean results of (a, d) interannual variability, (b, e) precipitation changes between the periods 1970–1998 and 1900–1929 and (c, f) ratio of precipitation change to variability. All results are shown for the wet season and as a percentage of the base period (1900–1929). For Figures 1b, 1c, 1e, and 1f, blue colours indicate a wettening and red colours a drying. For the white areas no data are available. Only land regions are shown.

a pattern of wettening of higher latitudes and tropics, and drying of the subtropics [*Trenberth*, 2011] is apparent in Figure 3b. The significant drying signals are generally more difficult to detect. One of the reasons for this is simply that the variability (noise) is large in the areas where drying is expected. However, even for the emergence of wettening, a global temperature increase of 1.4°C above early 19th century values is required. Following an A1B scenario this temperature level would be reached approximately by 2040 for a midrange of climate sensitivity. Note that the emergence of the signal depends substantially on the spatial averaging; the larger the area, the earlier the change is significant [*Masson and Knutti*, 2011]. In some regions the models either do not agree on the sign of change, or the

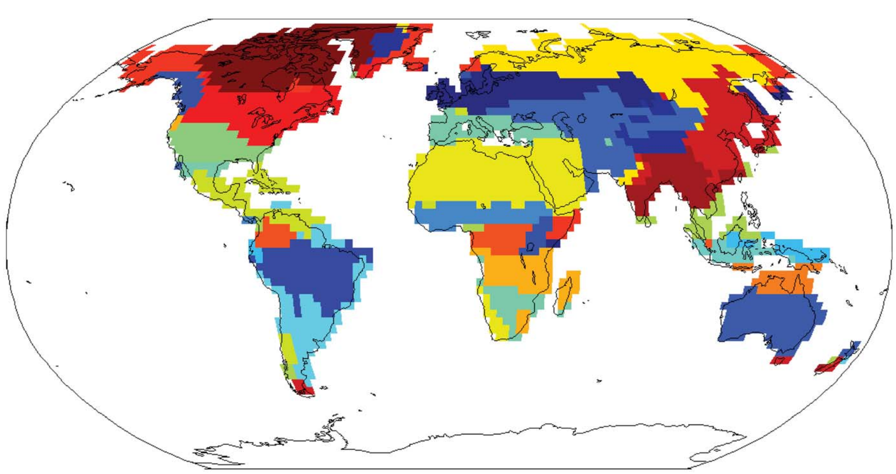

Figure 2. Twenty-four regions defined for annual precipitation defined by *Mahlstein and Knutti* [2010, Figure 4b]. Regions are defined using a cluster analysis that groups gridded model precipitation according to calculated future precipitation changes. Each colour shows a different region.

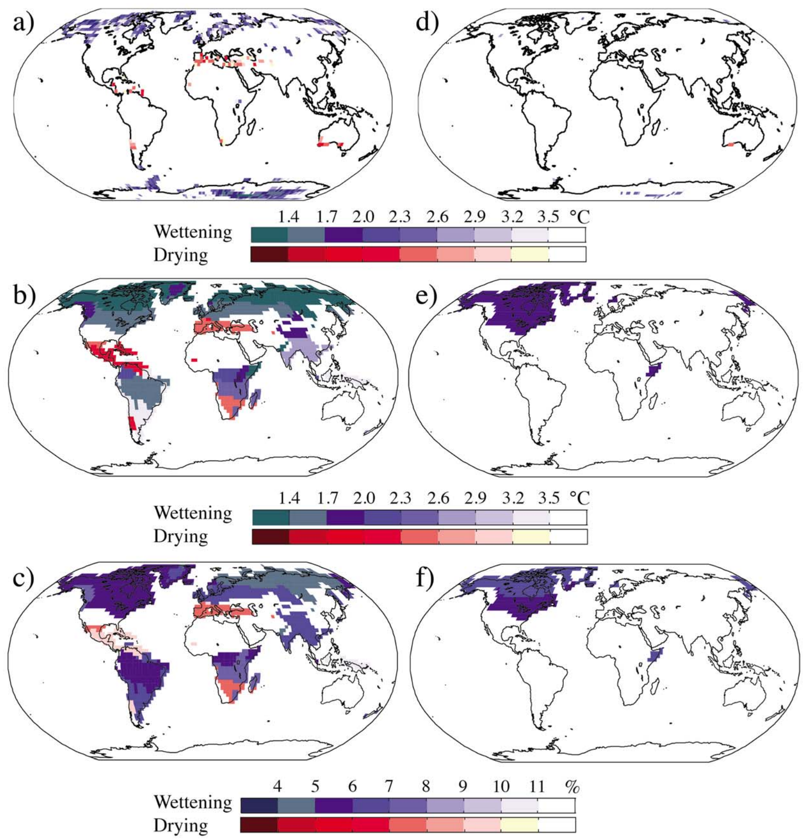

Figure 3. (a, d) Global temperature increase corresponding to the emergence of a significant precipitation change signal (above 1900–1929 levels) during the wet season on grid scale levels [°C], (left) showing the results for the 66% quantile (likely) and (right) showing the results for the 90% quantile of the models (very likely); (b, e) the same as Figures 3a and 3d but for the regions defined by *Mahlstein and Knutti* [2010] (see Figure 2 for regions); (c, f) precipitation changes in percentage [%] for the wet season at time of emergence compared to 1900–1929 wet season precipitation levels for the regions in Figures 3b and 3e. Blue colours indicate a wettening, red a drying, and white means no emergence of the signal before 2100. Shown are only results over land areas, and Antarctica is excluded in the regional results.

changes are not significant before 2100 for the required percentage of models. The disagreement on sign has often been misinterpreted as model errors, but where models do not report a significant change (mostly tropical regions) there is no reason to expect agreement on the sign of change [*Tebaldi et al.*, 2011].

[8] Figures 3c and 3f show the percentage changes in calculated WSP at the time of emergence. Again the given percentage of models is taken as a quantile of the distribution among the changes for all models. The change in WSP ranges from 4 to 11%, depending on the region and its climate variability. It is likely that a change this large can lead to large impacts on ecosystems and food production [*Naylor et al.*, 2007].

4. Discussion and Conclusions

[9] In larger geographical areas, such as zonal bands, detection of precipitation changes has already been reported [*Zhang et al.*, 2007]. *Min et al.* [2008] have also identified a human-induced moistening in the Arctic. Here, the Arctic is one of the earliest regions where significant precipitation changes during the wet season are simulated; however, we do not identify a significant modelled change for this region in the past. Several possible reasons could explain this different result. First, the pattern in our study is not scaled as is done in fingerprint detection studies [*Min et al.*, 2008] for the modelled results to match the observations. Second, the test applied in this study is rather conservative as the two time periods need to be statistically different at the 5% significance level and then the 66% or 90% quantile is used to determine global mean temperature of emergence. Finally, models tend to underestimate observed WSP changes relative to interannual variability and therefore display later emergence times based on the approach taken here.

[10] We find that widespread regional emergence of the signal of precipitation changes during the wet season is not anticipated in the near future based on current models. However, for large regions over land, it is likely that significant changes during the wet season will occur before the end of this century, with the first emergence of the signal occurring when the global temperature has increased by 1.4°C above 1900–1929 values. If 90% of the models (very likely) are required to exhibit a significant precipitation change during the wet season rather than 66%, then only a few regions display a statistically significant shift toward a wetter climate before 2100, and none of the regions demonstrate significant drying. Generally, drying during the

wet season is harder to detect than wettening, which can be explained by larger climate variability in the areas where drying is expected.

[11] Furthermore, our results also illustrate that models agree well on the sign of change in regions where emergence of the signal can be expected, because climate variability there tends to be relatively low. In most regions where no emergence is found in this century, climate variability is high. Thus, any agreement or disagreement between the sign of model projections is driven by noise [*Tebaldi et al.*, 2011].

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J. S. Daniel, I. Mahlstein, and R. W. Portmann, Earth System Research Laboratory, NOAA, 325 Broadway, Boulder, CO 80305, USA. (irina.mahlstein@noaa.gov)

R. Knutti, Institute for Atmospheric and Climate Science, ETH Zurich, Universitätstrasse 16, CH-8092 Zurich, Switzerland.

S. Solomon, Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, 77 Massachusetts Ave., Cambridge, MA 02139, USA.