Detection-attribution of global warming at the regional scale: How to deal with precipitation variability?

H. Douville

Météo-France, CNRM, Toulouse, France

Received 20 October 2005; accepted 1 December 2005; published 17 January 2006.

[1] Given the strong natural variability of precipitation, detection of anthropogenic climate change has been mainly based on surface thermal indicators. It is here argued that precipitation variability, whatever its natural or anthropogenic origin, is likely to affect surface temperature and, thereby, to hamper the detection-attribution of climate change at the regional scale. This issue is illustrated over Sudan and Sahel using the outputs of eleven coupled general circulation models having participated in the latest IPCC simulations. Like in situ observations, models show a strong relationship between detrended seasonal anomalies of surface air temperature and precipitation during the summer monsoon season. Linear regressions are then used to remove the precipitation influence on observed and simulated linear trends in surface air temperature. The results indicate that this strategy is efficient to reduce the spread in the simulated surface warming and make it more consistent with the instrumental record over recent decades.

Citation: Douville, H. (2006), Detection-attribution of global warming at the regional scale: How to deal with precipitation variability?, *Geophys. Res. Lett.*, *33*, L02701, doi:10.1029/2005GL024967.

1. Introduction

[2] Increasing evidence shows that the recent evolution of global surface air temperature (SAT) cannot be explained by natural climate variability and that most of the global warming that has been observed during the 20th century can be attributed to anthropogenic forcing [*Intergovernmental Panel on Climate Change* (*IPCC*), 2001]. At the regional scale, the signal to noise ratio is much weaker, which makes the detection and attribution of surface warming more difficult [*Spagnoli et al.*, 2002]. Moreover, the detection of anthropogenic changes in mean precipitation remains a difficult challenge [*Allen and Ingram*, 2002; *Hegerl et al.*, 2004]. Over recent decades, precipitation trends are small or mixed in many areas [*Adler et al.*, 2003]. In the tropics, they are generally positive over ocean but negative over land [*Kumar et al.*, 2004]. In the northern high-latitudes, they are generally positive when looking at the whole 20th century instrumental record [*Groisman et al.*, 2005]. At the regional scale, the natural variability of precipitation can be very strong and remains a major obstacle for the detection of climate change. Sub-Saharan Africa is the region that has experienced the strongest precipitation deficit since the late 1960's. Nevertheless, a partial recovery in annual rainfall has been recently observed and the natural versus anthropogenic origin of this deficit remains a matter of debate [*Brooks*, 2004]. Looking at recent climate scenarios, *Douville et al.* [2005] showed that the precipitation response to global warming is highly model-dependent not only at the regional scale, but even at the global scale due to model deficiencies in simulating the ENSO-precipitation teleconnections.

[3] Such uncertainties in both observed and projected precipitation trends are not only a problem for the detection of possible changes in the water cycle. Given its potential impact on the surface energy budget, precipitation is likely to have influenced temperatures trends at the regional scale [*Trenberth and Shea*, 2005]. If precipitation variability is not caused by the anthropogenic forcing or is not well captured in the climate scenarios, the detection of temperature change at the regional scale can be jeopardized. The objective is therefore to propose a simple strategy to correct SAT trends for the influence of the low-frequency variability of precipitation and, thereby, to provide more consistent estimates of surface warming between models and observations.

2. Data and Methods

[4] The relationship between summertime precipitation and temperature averaged over Sudan and Sahel [10–20°N/20°W–40°E] is explored in 11 coupled general circulation models (CGCMs) having participated in the recent IPCC4 intercomparison. The analysis is generally based on a single realization of the 20th century simulation and of the SRES-A2 21st century scenario, except for the NCAR model for which two additional replications of these experiments have been used to illustrate the importance of internal climate model variability at the regional scale. For the sake of simplicity, only the SRES-A2 family of climate scenarios has been considered. It describes a world of high population growth with relatively extreme assumptions about the future emissions of greenhouse gases (GHG). Nevertheless, these simulations are used here only to demonstrate the robustness of the precipitation-temperature relationship and not to predict climate change. Monthly timeseries of gridded SAT and precipitation have been extracted from the IPCC4 database (http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php) and concatenated from the late 19th century to the end of the 21st century.

[5] The focus of the study is on the possible modulation of the regional-scale surface warming by the low-frequency variability of precipitation. To demonstrate this, a simple linear regression between seasonal anomalies of precipitation and SAT has been estimated for each model.

0094-8276/06/2005GL024967$05.00

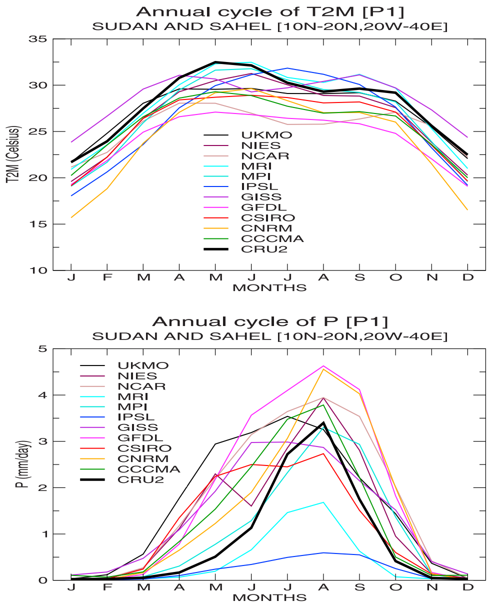

Figure 1. Mean annual cycle of (top) surface air temperature and (bottom) precipitation simulated and observed over Sudan and Sahel over the 1971–2000 (P1) period.

Before doing this, all timeseries have been detrended using a 3-order polynomial fit, to avoid that the regressions are based on coinciding long-term trends. Though very simple, polynomial fittings are relatively robust, do not require to specify a particular cut-off frequency, and are justified by the shape of the GHG concentration evolution prescribed in the simulations. Finally, the raw SAT and precipitation timeseries have been used to calculate raw linear trends over increasing time intervals of at least 30 years, and the previous regressions have been used to correct the SAT trends for possible trends in precipitation over the same interval.

[6] The same methodology has been applied to the instrumental record (although the 3-order polynomial fit has been replaced by a linear fit given the relatively short instrumental record). Two types of monthly mean climatologies have been used. The high-resolution (0.5°) CRU TS 2.1 climatology (CRU2 hereafter, available at http://www.cru.uea.ac.uk/cru/data) has been used to validate the mean SAT and precipitation simulated at the end of the 20th century. The low-resolution (5°) climatologies by *Jones and Moberg* [2003] (hereinafter referred to as CRUT2v) and *Hulme et al.* [1998], of SAT and precipitation respectively, have been used to compute the regression and trends. These data sets have been subject to homogeneity procedures and are much more suitable for detection studies than the CRU2 climatology which, in contrast, uses a larger number of observations but does not care for homogeneity. All climatologies have been interpolated onto a common 128 by 64 horizontal grid before analysis.

3. Results

[7] Figure 1 looks first at the mean annual cycle of SAT and precipitation averaged over Sudan and Sahel and over the 1971–2000 period. Compared to CRU2, most models are able to reproduce the transition between a cool and dry winter season and a warm and wet summer monsoon season. Note however that the maximum temperature is observed before the onset of the monsoon, a feature that is not captured by all models. Moreover, the onset is generally too early and the decay of the rainy season is too late. Finally, the peak of precipitation observed in July and August is sometimes poorly simulated. In the continuation of the study, the focus will be only on the summer monsoon season, which has been defined simply as the June to September (JJAS) season.

[8] Figure 2 shows the observed and simulated relationships between detrended anomalies of JJAS precipitation and SAT averaged over Sudan and Sahel. For each data set, three linear regressions have been calculated to demonstrate the robustness of the relationship. In keeping with observations, most models show a significant anti-correlation between precipitation and SAT, suggesting that stronger (weaker) monsoon precipitation is associated with cooler (warmer) SAT over Sudan and Sahel. This result is consistent with the cooling effect of the monsoon onset in Figure 1. Both latent heat (soil moisture) and radiative (cloud) fluxes explain the significant impact of precipitation on SAT, at both the seasonal and interannual timescales. Note however that the magnitude of the anti-correlation is highly model-dependent (-0.57 to -2.13°C/mm.day^{-1}) and is generally stronger than observed (-0.62°C/mm.day^{-1}). Note that all correlations shown in Figure 2 are statistically significant at a 5% level. The fraction of total variance that is explained by precipitation anomalies is 51% in the instrumental record, against 22 to 88% in the simulations. Only one model (IPSL) shows positive rather than negative correlations. The underestimation of monsoon rainfall (Figure 1) and therefore of precipitation variability probably contributes to mask the SAT sensitivity to surface evaporation in this model.

[9] Given the robustness of the relationships shown in Figure 2, the regressions are then used to remove the precipitation influence from the SAT trends calculated over the 20th century. The methodology is very simple. For a given time interval (at least 30 years), a linear regression is used to compute both SAT and precipitation trends averaged over Sudan and Sahel. Then, the black regressions shown in Figure 2 are used to correct the raw SAT trends for the influence of the estimated precipitation trends. The same procedure is applied for increasing time intervals ending in 2000, but starting in 1971, 1970, etc. . . . until the beginning of the simulations or of the instrumental record. The results are first shown (Figure 3) for three replications of the NCAR simulations, as well as for the CRUT2v observations. Looking first at raw trends in the observations, the shorter the period, the stronger the surface warming. This result is consistent with the increasing concentrations of GHG that have been observed over the 20th century. However, the maximum warming is obtained for a 45 to 50-yr time interval, as if the warming had been stabilizing or even weakening over recent decades despite the steady increase in GHG emissions. In contrast, corrected trends show a monotonous increase in SAT trends, i.e., an acceleration of surface warming, which is more consistent

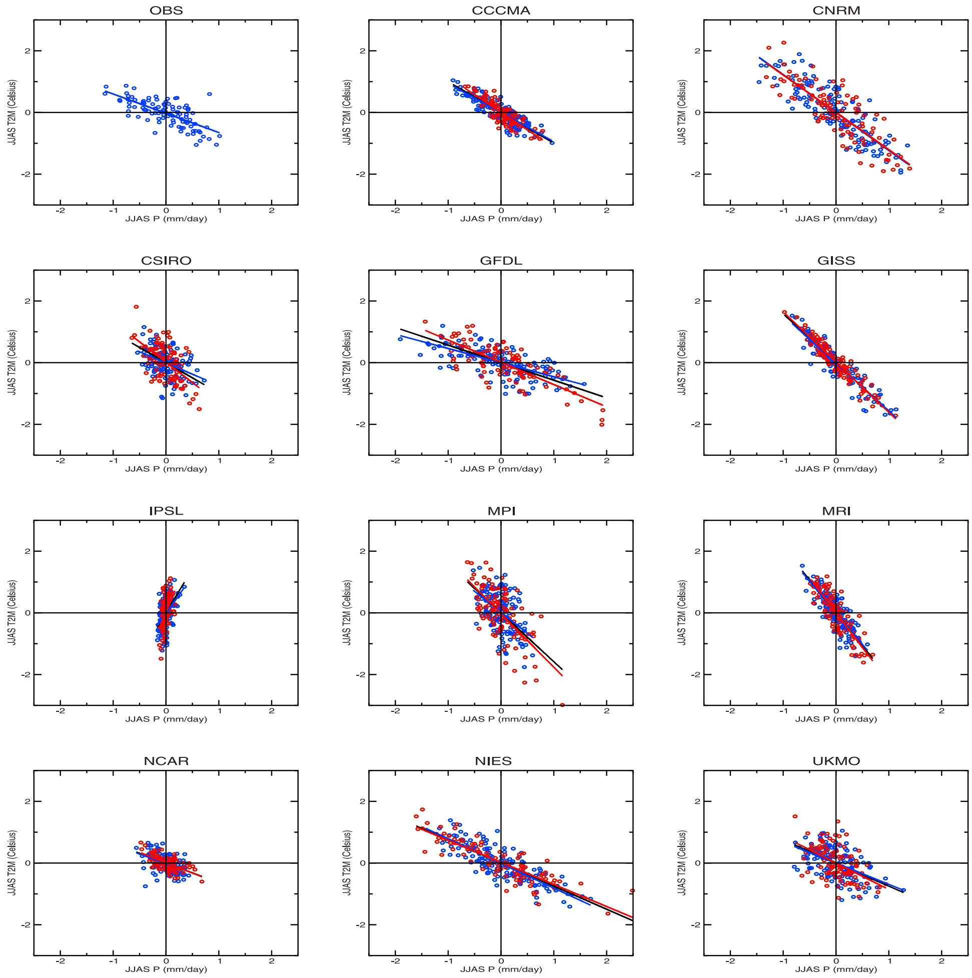

Figure 2. Scatterplots of JJAS surface air temperature versus JJAS precipitation anomalies in the observations and in the coupled simulations. All data sets have been first averaged over Sudan and Sahel and the resulting timeseries have been detrended. Blue symbols denote years before 2000, while red symbols are used for the 21st century scenarios. Three linear regressions are shown for the whole distribution (black line), the years before 2000 (blue lines), and the 21st century (red lines).

with the increasing radiative forcing. The low-frequency variability of precipitation is therefore responsible for the mid-1950's shift in the raw trends. Note also that corrected trends suggest a long-term cooling rather than warming over time intervals exceeding 70 years. This result should be however considered very cautiously given the poor instrumental record available in the early 20th century.

[10] Looking now at the trends simulated by the NCAR model, Figure 3 highlights the relevance of precipitation corrections for detecting and/or attributing climate change at the regional-scale. Though this model shows a relatively low SAT sensitivity to precipitation compared to the other models (Figure 2), the corrected trends are more robust and more consistent with observations than their raw counterparts. The relevance of precipitation correction is reinforced by Figure 4 that shows multi-model rather than multi-replication ensembles. In this case, 8 among the 11 models explored in the study are used to estimate multi-model ensemble mean SAT trends. Two models (CNRM and CCCMA) have been discarded due to their unrealistic global warming over the 20th century [*Douville et al.*, 2005] and the IPSL model has been also ignored given the unrealistic relationship that was found between precipitation and SAT in Figure 2. Once again, the corrected trends are more robust (less model-dependent) and more realistic than the raw estimates for time intervals varying between 30 and 60 years, i.e., the period with probably the best instrumental record.

4. Conclusion

[11] The strong influence of interannual precipitation variability on SAT averaged over Sudan and Sahel has been demonstrated and used to correct linear trends in SAT from corresponding trends in precipitation in both models and observations. The results indicate that this strategy is very efficient to reduce the spread in the simulated surface warming and make it more consistent with the instrumental record. This is not only the surface warming simulated over a specific period that is in better agreement with observations but also the temporal evolution of the SAT trends over the last 60 years, which is a much better signature of the GHG forcing than a static estimate of the surface warming. In contrast, the consistency between observed and simulated SAT trends is not improved for longer time intervals, probably due to the relatively poor instrumental record in the early 20th century. In the future, the same methodology could be applied over other regions where precipitation is likely to affect the land surface energy budget [*Trenberth and Shea*, 2005]. Grid cell rather than regional-scale regressions could be used to correct not only the time but also the space distribution of the SAT trends, and possibly provide regional patterns of surface warming with an enhanced signal-to-noise ratio. Moreover, progress in the detection of the regional precipitation response to global warming would be helpful to correct SAT trends only for the natural low-frequency variability of precipitation rather than for the whole variability as in the present study.

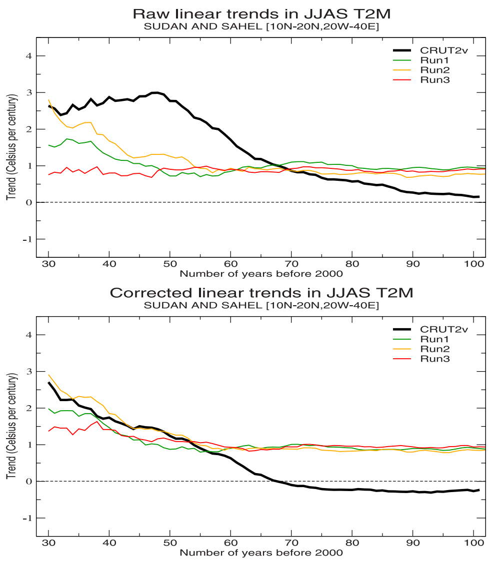

Figure 3. Raw and corrected linear trends in surface air temperature (in °C/century) averaged over Sudan and Sahel for increasing time intervals with a minimum of 30 years (1971–2000) and a maximum of 101 years (1900–2000). Black lines denote the observed trends, while the color lines correspond to three replications of the NCAR 20th century coupled simulations.

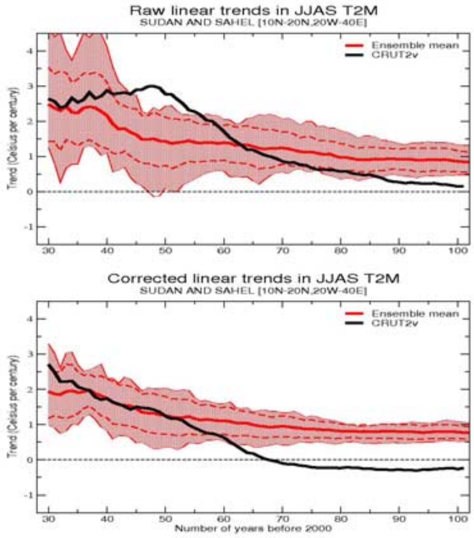

Figure 4. Same as Figure 3, but for a multi-model ensemble of 20th century coupled simulations. Besides the ensemble mean trends (thick red line), the spread among the models is illustrated though the minimum and maximum values (thin solid red lines) as well as plus/minus one standard deviation (thin dashed red lines).

[12] **Acknowledgments.** The author is grateful to all IPCC4 participants and to the PCMDI for the build up of the IPCC4 database. This work has been supported by the European Commission Sixth Framework Program (ENSEMBLES contract GOCE-CT-2003-505539).

References

Adler, R. F., et al. (2003), The version 2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present), *J. Hydrometeorol.*, *4*, 1147–1167.
Allen, M. R., and W. J. Ingram (2002), Constraints on future changes in climate and the hydrological cycle, *Nature*, *419*, 224–232.
Brooks, N. (2004), Drought in the African Sahel: Long term perspectives and future prospects, *Tyndall Cent. Work. Pap.*, *61*, 31 pp.

Douville, H., D. Salas Mélia, and S. Tyteca (2005), On the tropical origin of uncertainties in the global land precipitation response to global warming, *Clim. Dyn.*, doi:10.1007/S00382-005-0088-2.
Groisman, P. Y., et al. (2005), Trends in intense precipitation in the climate record, *J. Clim.*, *18*, 1326–1350.
Hegerl, G. C., F. W. Zwiers, P. A. Stott, and V. V. Kharin (2004), Detectability of anthropogenic changes in annual temperature and precipitation extremes, *J. Clim.*, *17*, 3683–3700.
Hulme, M., T. J. Osborn, and T. C. Johns (1998), Precipitation sensitivity to global warming: Comparison of observations with HadCM2 simulations, *Geophys. Res. Lett.*, *25*, 3379–3382.
Intergovernmental Panel on Climate Change (IPCC) (2001), *Climate Change 2001: The Scientific Basis: Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, edited by J. T. Houghton et al., 881 pp., Cambridge Univ. Press, New York.
Jones, P. D., and A. Moberg (2003), Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001, *J. Clim.*, *16*, 206–223.
Kumar, A., F. Yang, L. Goddard, and S. Schubert (2004), Differing trends in the tropical surface temperatures and precipitation over land and oceans, *J. Clim.*, *17*, 653–664.
Spagnoli, B., S. Planton, M. Déqué, O. Mestre, and J. M. Moisselin (2002), Detecting climate change at a regional scale: The case of France, *Geophys. Res. Lett.*, *29*(10), 1450, doi:10.1029/2001GL014619.
Trenberth, K. E., and D. J. Shea (2005), Relationships between precipitation and surface temperature, *Geophys. Res. Lett.*, *32*, L14703, doi:10.1029/2005GL022760.

H. Douville, Météo-France, CNRM/GMGEC/UDC, 42 avenue Coriolis, F-31057, Toulouse Cedex 01, France. (herve.douville@meteo.fr)