An event attribution of the 2010 drought in the South Amazon region using the MIROC5 model

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Received: 25 January 2013 Revised: 7 April 2013 Accepted: 18 April 2013

Abstract

We produced 100-member event attribution ensembles during 2009–2012 under all forcing conditions and in two different counterfactual worlds without anthropogenic forcing (mainly greenhouse gases and aerosols) and without aerosol emission changes using the MIROC5 atmospheric general circulation model. It seemed that both human influences and the sea surface temperature (SST) natural variability increased probabilities of the 2010 severe drought in the South Amazon region, and that changes in aerosol emissions had little effect on the drought. It should be noted that our assessments were sensitive to bias corrections according to the relationships between the SST natural variability and precipitation.

Keywords: attribution; climate change; drought

1. Introduction

When high-profile climate and weather events occur, climate scientists are asked whether those events are caused by human activity. In principle, it is impossible to answer whether specific climate and weather events are attributable to anthropogenic climate change. However, it is possible to investigate whether human activity has changed the probability or magnitude of climate events (Allen, 2003). Such event attributions present new challenges for detection and attribution studies of climate change.

Stott et al. (2004) conducted the first study that applied the formal attribution technique (Allen and Tett, 1999) based on comparisons between observed data and historical climate simulations with and without human influence from a coupled Atmosphere Ocean General Circulation Model (AOGCM). They suggested that human influence has at least doubled the risk of a heat wave exceeding the 2003 European event.

Pall et al. (2011) applied another approach using an Atmosphere General Circulation Model (AGCM) to produce probability density functions (PDFs) of climate variable anomalies with and without changes in anthropogenic greenhouse gas emissions (GHGs), suggesting that GHGs increased the risk of floods in England and Wales in the autumn of 2000. They performed real climate runs of the AGCM driven by the observed values of anthropogenic and natural forcing agents and by the observed sea surface temperature (SST) and sea ice cover (ICE). They also produced counterfactual non-GHG change climate runs driven by pre-industrial GHG concentrations and with observed values of SST and ICE cooled according to estimates of the attributable warming from historical anthropogenic GHG emissions, with other forcing agents remaining at observed values.

The event attribution studies noted above depend on models and estimates of counterfactual external conditions. Therefore, event attribution estimates may be sensitive to uncertainties and biases in these factors. To investigate the sensitivities of assessments, Pall et al. (2011) and Christidis et al. (2013) used several different estimates of counterfactual SST and ICE conditions while utilizing single AGCMs. Christidis et al. (2012) compared the different assessments of sub-continental-scale temperature changes based on two AOGCMs. It is informative to compare the outputs from several models and several estimates of counterfactual external conditions. Several research centres around the world agreed to perform AGCM simulations similar to those of P11 in the same time period (year 2010 and onwards). This project is called the Attribution of Climate-related Events (ACE; Christidis et al., 2013).

To contribute to the ACE project, we used the MIROC5 AGCM (Watanabe et al., 2010) and developed a new system for extreme climate event attribution. A goal of this paper is to describe the experimental setups of the MIROC5 event attribution system. Using this system, we produced a real climate initial condition perturbed ensemble during the June 2009 to August 2012 period. We also produced other counterfactual ensemble without anthropogenic influences. The designs of these ensembles are generally based on the ACE project, although there are some differences in the experimental design details between the modelling centres. Furthermore, we produced an ensemble without changes in the carbon and sulphate aerosols...
emissions. This additional ensemble enables us to estimate the possible effects of anthropogenic aerosols on climate events.

For the first study of these ensembles, we investigated the possible influences of human activity on the probability of the 2010 drought event in the South Amazon (SA; Lewis et al., 2011). Marengo et al. (2011) suggested that the 2010 drought was mainly related to the Atlantic North–South Gradient (ANSG) of the SST. The large positive ANSG (warmer anomalies in the tropical North Atlantic Ocean than in the South) led to a northward replacement of the intertropical convergence zone, mainly resulting in severe drought during the austral winter dry season (also see Good et al., 2008; Yoon and Zeng, 2010), where the drought began in the previous austral summer wet season due to El Niño. La Niña in the winter may slightly counteract the drying resulting from the positive ANSG. Although these suggestions are based on analyses of observed data, it is not yet clear whether the natural variabilities in the SST deterministically affect the precipitation anomalies in the SA. It has also been suggested that future SST trend patterns like the ANSG and El Niño Southern Oscillation (ENSO) will induce large effects in the SA precipitation and runoff changes (Shiogama et al., 2011), whereas these trends are intrinsically different from the corresponding natural variability. Cox et al. (2008) suggested that future decreases in the sulphate aerosol emissions in the North Atlantic Ocean will lead to more positive ANSG-like SST trends and enhance severe droughts. Booth et al. (2012) suggested that previous generations of AOGCMs without indirect aerosol effects underestimated historical aerosol cooling over the North Atlantic Ocean. We discuss the possible effects of anthropogenic factors, including aerosol emission changes, on droughts. Biases in the model simulations of the climate events discussed can significantly affect attribution estimates. We tested the sensitivities of event attribution estimates to bias corrections.

2. Simulations

We used the MIROC5 AGCM with a resolution of T85L40 (Watanabe et al., 2010) to produce the following ensembles:

- ALL-long (ALL forcing Long period runs): We integrated ten-member historical runs for the years 1949–2011. The AGCM was driven by the observed SST and ICE (HadISST) (Rayner et al., 2003) and the historical anthropogenic (GHGs, sulphate and carbon aerosols, tropospheric and stratospheric ozone, and land use change) and natural (solar irradiance changes and large volcanic activity) forcing factors (the 2006–2011 period runs were under the Representative Concentration Pathways 4.5 scenario). For the first member, we performed a spin-up run for the 1946–1949 period. For the other members, we took the initial conditions from the first member with 1-year intervals, and changed the date of the data to 1 January 1949.

- NAT (NATural forcing runs): The 100-member ensemble runs were produced under the natural external conditions for the period from June 2009 to August 2012. The anthropogenic forcing factors were fixed at the year 1850 conditions. Anthropogenic signals on the SST and ICE were removed. We estimated the anthropogenic SST signals (Figure 1(a)) as follows: we computed the ten-member averages of the monthly SST anomalies from the anthropogenic forcing runs using the MIROC3 AOGCM under the historical (1850–2000) and A1B (2001–2030) scenarios (Shiogama et al., 2012); we applied an approximately 3000 km spatial filter and 11-year running averages for each calendar month SST anomaly from the climatology of a pre-industrial control run to reduce the influences of natural variability. The anthropogenic ICE signals were estimated based on empirical linear relationships between the SST and ICE in the HadISST grid-point data for each Hemisphere as in P11. We took the initial conditions from a single 3.5-year spin-up run under the natural external conditions with 6-h intervals.

- noCS (no Carbon and Sulphate aerosol runs): The 100-member ensemble runs were produced under the external conditions of all forcing with the carbon and sulphate aerosols emissions at the pre-industrial values. Carbon and sulphate aerosol signals in the SST and ICE were estimated from the four-member carbon and sulphate aerosol forcing runs of MIROC3 (Shiogama et al., 2012) (Figure 1(b)). Because MIROC3 includes indirect aerosol effects (Shiogama et al., 2010), there were large aerosol cooling over the North Atlantic Ocean (c.f. Booth et al., 2012). We took the initial conditions from a single 3.5-year spin-up run under the external conditions without changes in the carbon and sulphate aerosols over 6-h intervals.

We compared the model simulations with the precipitation observations from the Global Precipitation Climatology Project (GPCP) (Adler et al., 2003). Here, we discuss only the July to October mean precipitation anomalies, although precipitation intensity, time without rain, soil moisture, and river runoff are also important drought indicators. The analyzed period is July to October in 1979–2010. We defined the SA region as 85°W–20°W, 25°S–0 S (Figure 1). We defined the index of the ANSG as the SST anomalies (relative to the 1979–2010 mean) averaged over 80°W–15°W, 6°N–22°N, minus that over 40°W–20°W, 25°S–5°S. The ENSO index is
the SST anomalies averaged over the Nino 3.4 region (170°W–120°W, 5°S–5°N).

3. Results

Figure 2 shows the observed and simulated distributions of the July to October precipitation anomalies in the SA region. The MIROC5 AGCM accurately simulates the 1979–2010 precipitation anomaly distribution (black and grey curves). Therefore, with this simple first-order evaluation, it seems that bias correction is not necessary. The probabilities of drought events more at least as severe as the 2010 record are noCS (1/100 = 1%) ≈ ALL (1%) > NAT (0%). These findings suggest that without bias corrections, the 2010 record was a very rare event given the ALL-forcing climate conditions.

To further evaluate the model, we analyzed the multivariable regression maps of the precipitation anomalies onto the ANSG and ENSO indices during the 1979–2010 period (Figure 3). The MIROC5 model generally represented well the precipitation responses to the ANSG and ENSO in the regions where the precipitation responses to these natural SST variabilities are large, such as the northeast coast region of South America, the tropical Pacific Ocean, and the north subtropical region of the Atlantic Ocean. However, there were nonnegligible biases in the smaller responses of the precipitation to the ANSG and ENSO in the western SA region.

The multivariable regressions of the average SA precipitation anomalies (Prec_obs and Prec_mdl for the observations and the ALL-long ensemble average, respectively) onto the ANSG and ENSO indices are:

\[
\text{Prec_obs} = -4.36 < -6.28, -2.68 > \text{ANSG}
+0.02 < -1.71, 1.83 > \text{ENSO} \quad (1)
\]

\[
\text{Prec_mdl} = -3.27 < -4.46, -2.06 > \text{ANSG}
-4.50 < -5.77, -3.15 > \text{ENSO} \quad (2)
\]

where all the terms were detrended and the ANSG and ENSO indices were normalized. In the right-hand side terms, we computed best-estimates and uncertainty ranges of scaling factors (50% < 10%, 90% >) by applying the following methods: (1.1) for Equation (1), at first, we calculated the scaling factors and the best-fit two-dimensional plane of the regression; (1.2) the residuals of Prec_obs from the best-fit plane were computed; (1.3) we randomly selected 32 samples from the 32-year length residuals (i.e., we assumed 1 degree of freedom for each 1 year sample); (1.4) we

Figure 2. The black and ten grey curves are PDFs of the July to October precipitation anomalies (%) relative to the 1979–2010 mean) during the 1979–2010 period for the observations and ALL-long, respectively. The PDF is calculated as a normalized histogram of samples within half-overlapped 6%-width bins. The black vertical line is the 2010 observation. The green, blue, and red curves indicate the PDFs of the ALL, NAT, and noCS runs, respectively. Note that these PDFs were calculated from different numbers of samples: 32 for the observations and ALL-long, and 100 for ALL, NAT, and noCS.
Figure 3. The left panels show the multivariable regression maps of July to October precipitation anomalies on (a) the ANSG index (%) and (c) the ENSO index (%) for the observations. Solid boxes are the definition areas of the ANSG and ENSO indices. The dashed-line boxes indicate the SA region defined in this study. The right panels are the multivariable regression maps of July to October precipitation anomalies on (b) the ANSG index (%) and (d) the ENSO index (%) for ALL-long.

added the randomly selected residuals to the best-fit plane; (1.5) we computed scaling factors of regression of the data from the step (1.4); (1.6) we repeated the steps (1.3)–(1.5) 1000-times; (1.7) finally 50% < 10%, 90% > values of the histogram of the 1000 scaling factor samples were considered as the best estimates and the uncertainty ranges; (2.1) for Equation (2), at first, we randomly choose ten samples from the ten ensemble members; (2.2) the ensemble averages of the ten samples were computed; (2.3) we applied the same procedures as the steps (1.1)–(1.5); (2.4) we repeated the steps (2.1)–(2.3) 1000-times; (2.5) finally 50% < 10%, 90% > values of the histogram of the 1000 scaling factor samples indicated the best estimates and the uncertainty ranges.

Although the MIROC5 model might underestimate the drying due to the positive ANSG, the difference between the model and observations was not significant. Whereas the ENSO did not have significant impact on the dry season SA averaged precipitation in the observations (c.f. Yoon and Zeng, 2010), the MIROC5 model simulated the significant wetting due to La Niña (the ENSO index is negative) in the July to October period of 2010.

To correct these second-order biases in the ANSG/ENSO-precipitation relationships, we removed the precipitation anomalies computed by Equation (2) from the precipitation anomalies of the ALL, NAT, and noCS ensembles and added those from Equation (1). Figure 4 shows the results of the bias corrections using the best estimates of the scaling factors. The bias corrections in the small drying underestimation due to the positive ANSG (Figure 4(a)) and the wetting overestimation due to La Niña (Figure 4(b)) lead to increases in the severe drought probability (Figure 4(c)). The probabilities of drought at least as severe as the 2010 record are noCS (16% < 4%, 30% >) ≈ ALL (15% < 5%, 32% >) > NAT (2% < 1%, 11% >), where the 50% < 10%, 90% > values were estimated using the 1000 scaling factor samples of Equations 1 and 2. Although the precipitation PDF of the ALL-long runs is good, the bias corrections in the precipitation-SST relationships have large impacts on the attribution estimates. An important finding is that with the bias corrections, the probability of 2010-like events is larger than 10% (in the best estimates) given the ALL-forcing climate conditions. Anthropogenic factors increased the drought frequency by more than threefold (ALL/NAT = 6.3 < 3.2, 8.7 >). Changes in the carbon and sulphate aerosols had little impact, at least in this model (noCS/ALL = 1.0 < 0.8, 1.1 >).

The spread of the 2010 ALL PDF is not much smaller than that of the ALL-long PDF in Figure 2, suggesting that the SST variability influences on the SA precipitation are not deterministic but conditional. We estimated the precipitation PDFs with neutral...
We computed the initial condition perturbed ensemble during June 2009 to August 2012 period under all forcing conditions and in two different counterfactual worlds without anthropogenic forcing and without carbon and sulphate aerosol emission changes. By analyzing these ensembles, we found that both anthropogenic warming and the SST natural variability have increased the probability of the 2010 drought event in the SA region. Anthropogenic aerosols did not have large effects on the drought, at least in this model.

However, it should be noted that these suggestions are based on a particular bias-correction process. Here, we applied simple bias corrections on the relationship between the SST variability and the precipitation anomalies. As shown in Figure 4, the attribution estimate of severe droughts is sensitive to this bias-correction process. For more severe extreme events over finer spatial and temporal resolutions, models tend to have larger biases (Allen and Tett, 1999; Wehner et al., 2010). Therefore, the model evaluation and bias correction should be further studied to provide a robust attribution estimate of the extreme events of public interest. Additionally, it should be noted that the above assessments are based on a particular event attribution system. We used only GPCP as precipitation observations. There are nonnegligible uncertainties in precipitation observations over the SA region (Yoon and Zeng, 2010). Testing attribution result sensitivities to changes in the event attribution system and observed data remain for future work.

Acknowledgements

We appreciate useful comments from C. Jones, D. Stone, and the reviewer. This work was supported by the Program for Risk Information on Climate Change (SOUSEI program) and Grant-in-Aid 23310014 from the Ministry of Education, Culture, Sports, Science and Technology of Japan and the Environment Research and Technology Development Fund (S-10) of the Ministry of the Environment of Japan. Earth Simulator and NEC SX (NIES) were utilized for the simulations.

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4. Summary and discussion

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