COMMENTARIES

EARTH SCIENCES

Reducing model biases is essential to projecting future climate variability

Extreme El Niño events not only cause climate disasters leading to enormous socioeconomic losses, but also have devastating impacts on the world's ecosystems [1,2]. A reliable projection of their frequency change in the future warmer climate is therefore very important for our sustainable development as well as disaster prevention [3].

Since the development of extreme El Niño is always accompanied by weakened easterlies and eastward extension of deep convection, a commonly accepted view is that the extreme El Niño, which is defined with convective activities in the Niño3 region, would increase twice in the future warmer climate [4]. Because the sea surface temperature (SST) warming in the eastern tropical Pacific would be faster than its surrounding areas, the climatological zonal and meridional SST gradients, preventing the deep convection from moving eastward in the present-day climate, would be easily reversed by a much smaller-than-today SST anomaly in the eastern tropical Pacific in future.

However, the projected 'El Niño-like' SST warming in the tropical Pacific has been often questioned [5] for two main reasons: (i) the winner of the competition between the weakening of the Walker circulation due to the increased atmospheric static stability [6] and the strengthening of easterly winds due to oceanic thermostat mechanism in future [7,8] is still unknown [5,9]; and (ii) the remarkably distinct tropical Pacific SST trend between model simulations and observations over the past [10–13] highlights the existence of systematic model biases in CMIP5. Accordingly, a key question is raised: Would the tropical eastern Pacific warm faster than its surrounding areas?

In this issue, Tang *et al.* [14] make it clear for the first time that models' common biases may have great impacts on the projection of future tropical Pacific SST change. By identifying 13 common biases in simulating the past climate, they suggest the SST warming in the tropical eastern Pacific may be largely over-projected. Surprisingly, the SST change after correcting the impacts of the models' common biases shows that the strongest warming occurs in the tropical western Pacific rather than in the east, accompanied by stronger easterlies and suppressed convection in the eastern Pacific. This shows a stark contrast to the original CMIP5 projection.

Interestingly, Tang *et al.* [14] suggest the originally projected two-fold increase of extreme El Niño is mostly determined by the mean-state change, while the anomaly itself would not change much. This view is supported well by the almost identical probability density distribution of Niño3 SST anomaly (Fig. 1) Therefore, the result indicates that the originally projected two-fold change in the extreme El Niño frequency defined by total values may be largely due to the models' common biases in the projection of mean-state changes. Even though the complex interactions between mean state and El Niño/Southern Oscillation may influence such a statistical correction, the results of Tang *et al.* [14] assert that a reliable projection of the future extreme El Niño frequency change requires the correct mean-state projection. Indeed, Zhao and Fedorov [15] have recently suggested that the ENSO would be suppressed due to the enhanced east-minus-west SST gradient, associated with the strengthened easterlies.

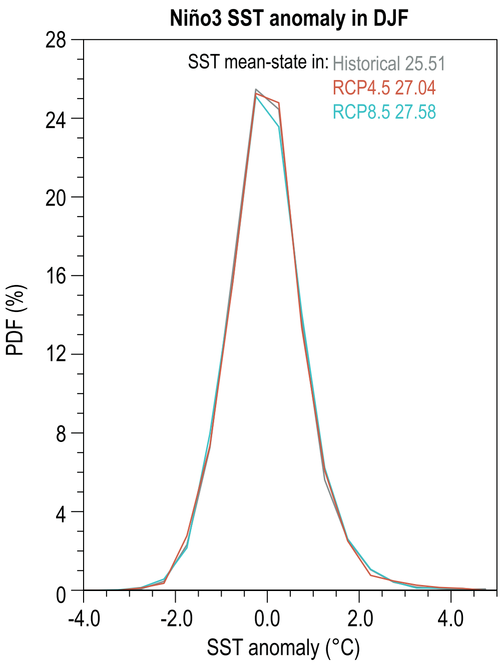

Figure 1. The probability density distribution of Niño3 SST anomaly in boreal winter. The gray, red and blue curves denote the results based on the historical simulations, RCP4.5 scenario and RCP8.5 scenario, respectively. The multimodel ensemble means of Niño3 SST climatology in the three experiments are also displayed. Results are produced based on the 28 CMIP5 models analyzed in Ref. [14]. PDF: probability density distribution. DJF: December, January and February. SST: sea surface temperature.

In summary, the findings of Tang *et al.* [14] shed a new light on the importance of correcting systematic biases before getting reliable projection on future climate variability. More efforts are certainly necessary to reduce climate models' common biases in coming years.

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The role of systematic errors

General circulation models (GCMs) have progressed enormously over the last few decades and they have allowed huge advances in forecasting at every timescale, from daily to seasonal and decadal, and in climate simulations of the Earth climate system. These advances have increased the relevance of the results for decision-making and the drafting of strategies and policies with far-reaching impacts. In fact, they provide the foundation of the global conversation on climate change mitigation and adaptation. Even the complex international negotiation, taking place in the context of the Paris Agreement and the UN Framework Convention on Climate Change, is ultimately based on science obtained mostly with global and regional models.

It is not surprising then that the issues of the accuracy, fidelity and reproducibility of these results are of foremost importance. Deviation from reality in models occurs either as a random effect, i.e. different from simulation to simulation as a result of the sensitivity of the system nonlinear interactions to perturbations, or as a systematic deviation, showing in every simulation and usually typical of a certain model. The latter is also known as 'systematic error' and sometimes 'bias'. The systematic error can present itself as a deviation of the mean or as a systematic misrepresentation of some of the statistics of the system, for instance as an over- or underestimation of frequency and intensity of particular events.

Certain errors are particularly stubborn. The double Intertropical Convergence Zone (ITCZ) has plagued GCMs for a long time and it is resistant to improvements in resolution and formulation [1,2] and in the Atlantic has affected forecasting skills [3,4]. The systematic error is probably just a symptom of various inaccuracies and/or errors that ultimately show in a specific form, but they can affect not only at the local level but also through remote teleconnection. For instance, the double ITCZ can affect climate variability outside the tropics [5]. GCMs provide also the basic information for all the studies aiming at localizing information, for instance as boundary condition in regional models, and in this way the systematic error can propagate into downscaling exercises [6]. It is increasingly evident how the influence of this error can be pervasive through the entire climate enterprise.

It seems reasonable that a good understanding of the causes and effects of systematic errors is of utmost importance for weather and climate investigations, especially if the assessment has to become the basis for policy formulation or implementation measures. It simply cannot be ignored and it is crucial to define the limits and content of our knowledge. In this issue, Tang *et al.* [7] provide a nice example of an investigation that takes systematic error into consideration for a problem that is particularly relevant to planning for adaptation to climate change and to a correct evaluation of the connected risk. ENSO variability has large impacts at seasonal scale in many areas of the world and understanding its evolution under global change is central to the definition of the adaptation strategies.

ENSO is identified usually as a deviation from the climatology, i.e. a long-term mean state, but climate change will act on both the mean and the variability. So, it is an issue if criteria based on present-day thresholds can still be used in climate projections and what is the best strategy to modify them to give an accurate representation of ENSO in a changing climate.

The systematic error has proven to be resistant and chances are that it is not going to go away any time soon. Barring sudden breakthroughs, we will have to find ways to go around it and to assess correctly its impacts on processes and on the predictive skill. The most promising opportunities to deal with systematic errors are offered by the rapid developments in recursive data exploration, machine learning and powerful nonlinear analysis techniques that are currently underway. The combination of advanced GCMs and sophisticated data exploration will probably give us the best opportunity to tackle this stubborn problem.

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