Published in final edited form as:

Chance (N Y). 2017 ; 30(4): 19–25. doi:10.1080/09332480.2017.1406755.

Climate model intercomparison

Mikyoung Jun [Associate Professor]

Department of Statistics at Texas A&M University

Study on climate change

Despite some climate “skeptics” regarding global warming and climate change due to human influence, it is safe to say that scientific consensus has been achieved and the majority of the public believe that it is real. We observe that global surface temperature keeps rising and that arctic sea ice is rapidly shrinking. Numerous scientific research studies report that the increase in global surface temperatures is due to human-induced emission of greenhouse gases. However, since we can only observe the past and present climate, we need tools and methods for accurate prediction of future climate change. Furthermore, it is not just temperature or precipitation but rather numerous climate variables that vary and interact together over space and time. Thus, we need sophisticated tools and methods for understanding the current climate and forecasting the future climate as accurately as possible.

What are global climate models?

Coupled Atmospheric and Ocean General Circulation Models (AOGCMs, commonly called *climate models* or *global climate models*) are complex systems of partial differential equations to simulate the climate in a 4-dimensional domain: surface of the Earth (2-dimensional) $\times$ vertical height (or pressure) $\times$ time. The models are called “coupled” since the atmospheric and ocean components interact in a complex manner (for instance, sea surface temperature information is fed into the atmospheric component, and atmospheric wind stress information is fed into the ocean component).

The outputs of these climate models are the values of multiple climate variables (temperature, precipitation, radiation, relative humidity, wind pressure, etc.) on a gridded domain (latitude $\times$ longitude $\times$ vertical height or pressure; see Figure 1) across time. They also involve several submodels, such as a sea ice model. Many physical processes are parametrized; there are thousands of parameters for physical processes such as solar radiation, convection, and cloud cover. The inset in Figure 1 shows only a few examples of the physical processes that go into a global climate model.

About the author

Mikyoung Jun is an Associate Professor in the Department of Statistics at Texas A&M University. She received her PhD in statistics from University of Chicago in 2005. Her main research interests are development of statistical models for physical processes on a global scale and their applications to various climate applications.

These coupled AOGCMs are the main sources of information for understanding the climate in general and especially for predicting future climate change (since we do not have data from the future!). Another use of these models is that we can simulate the effect of greenhouse gases on the future climate. For example, by varying emission scenarios (how much greenhouse gas gets emitted into the air), we can learn how much surface temperature will increase (or decrease) given an emission scenario for the future.

Along with the great endeavors made in developing global climate models, serious effort has been devoted to developing Regional Climate Models (RCMs). RCMs are similar to global climate models, but they are forced by specified lateral and ocean conditions from a global climate model or observation-based dataset. They account for high-resolution topographical data, land–sea contrasts, surface characteristics, etc. They only cover a limited domain, and the values at their boundaries are specified. Figure 2 provides an illustration showing the differences in horizontal and vertical grid resolutions between a global climate model and an RCM over a spatial region.

Are climate models accurate?

Climate models are essential tools in climate study. They are used for weather forecasting and understanding the past and present climate and are irreplaceable tools for understanding climate change. They are huge systems and cost billions of dollars to be developed and to be run on supercomputers.

Climate models improve over time, owing to tremendous efforts on the part of scientists and climate modelers around the world. However, they are still far from perfect. Although numerous state-of-the-art climate models have been developed by top-notch scientists and climate modelers, they often give very different answers regarding certain aspects of the climate.

Some of these differences may be due to the climate system's internal variability (due to natural internal processes within the climate system). There is also the climate system's external variability (due to natural and anthropogenic external forcing). Forcing refers to a change in the net energy exchange between the climate system and the environment, such as solar intensity cycles, anthropogenic emissions of greenhouse gases, and volcanic eruptions. The volcanic and solar forcing reconstruction by climate models may differ. There are also aerosol effects that climate models may get wrong. Aerosol can affect climate in several ways. For instance, aerosols can reflect incoming sunlight back to outer space when the sky is clear, and it can also trap solar energy within the atmosphere. Climate models incorporate the effects of aerosols on clouds through parametrizations, and thus problems in these parametrizations could result in incorrect projections of climate.

It is widely acknowledged that current versions of climate models have great room for improvement. There are regions such as sea ice regions where climate models suffer more than in other areas, and there are climate variables such as precipitation for which climate models have a much harder time, compared to other climate variables such as surface

temperature. Therefore, a thorough understanding and validation of these climate models is imperative.

CMIP and climate model intercomparison

The Intergovernmental Panel on Climate Change (IPCC, <http://www.ipcc.ch>), established by the United Nations Environment Programme (UNEP) and the World Meteorological Organization (WMO) in 1988, publishes Assessment Reports (ARs) on climate change based on results from various AOGCMs developed by multiple organizations worldwide.

The Coupled Model Intercomparison Project (CMIP) is an experimental protocol established in 1995 by the World Climate Research Programme (WCRP), under the United Nations, for climate model diagnosis, validation, intercomparison, documentation, and data access. A large body of members of the international climate modeling community is participating, and much of the CMIP data are archived and publicly available from the Program for Climate Model Diagnosis and Intercomparison.

Phase three of the CMIP (CMIP3), which provided materials for the IPCC's fourth Assessment Report (AR4), included about 20 climate models and completed the data for the archives, mostly in 2005 and 2006. The number of climate models participating in the next phase, CMIP5, was much greater, and the performance of each of these climate models was shown to be generally better than those of CMIP3. The archive for CMIP6 is currently underway.

Scientific publications have noted that there are often significant disagreements between the climate models participating in CMIP3, as well as its successors. For example, the projected global temperature increase in 2100 and thereafter can vary by more than 1 degree (see Figure 3). The "accuracy" of climate model outputs may mean different things; it might be about the "mean" (i.e., the center) of the prediction to some people and about the "uncertainty" (i.e., the spread) to others. At any rate, one might expect to see smaller uncertainty from one CMIP generation to the next in terms of how similar or different the climate models are in that generation.

However, according to Knutti and Sedlacek (2012), this is not the case. The authors show that the uncertainty (or spread) in CMIP5 models is comparable to the uncertainty in CMIP3 models. This rather disappointing "improvement" in CMIP5 models over those in CMIP3 does not necessarily mean that the models did not get better. It may well be due to the fact that the climate models became more complicated (for example, more forcing terms and aerosol were added to the models in CMIP5). Knutti and Sedlacek (2012) also note that direct comparison of the models in CMIP3 and the models in CMIP5 is not possible, since the two generations use different emission scenarios. They further argue that there are many other factors that contribute to model disagreements, such as (i) the inherent limitation of computational resources, (ii) lack of a complete scientific understanding of climate, (iii) lack of long-term observations (our observation records for the climate do not go back further than the 1800s, and satellite data have only become available since around the 1970s), and

(iv) lack of consensus on the metric to use to determine how similar or dissimilar model outputs are.

Despite the complexity of climate models and their vast amounts of output, common practices for validating model outputs and comparing across different climate models rely on simple spatial or temporal means and variances. With the advancement of spatial and spatio-temporal methods in statistics, statisticians can go beyond the current common practice in order to better understand the spatial and temporal variation structures of climate model outputs. In particular, statistical techniques for multivariate spatial and spatio-temporal distributions allow statisticians to validate climate model outputs considering multiple climate variables jointly at various spatial and temporal scales (i.e., how one climate variable covaries in space and/or time with other climate variables and how they interact in space and/or time).

One example is the work of Philbin and Jun (2015), who consider surface temperature and precipitation jointly and focus on validating climate models in terms of how well they produce the joint distributional structure of the two climate variables. They treat each climate variable (30-year seasonal averages from 1981 to 2010) as spatial data and estimate key (statistical) parameters that jointly describe the spatial variations of the two climate variables. In addition to comparing those (statistical) parameter estimates across different climate models, they also compare them with the (statistical) parameter estimates of observations. The idea behind this is that, if each climate model represents something more or less similar to the “true” climate (in this case, the observations are considered to be the truth, subject to measurement error), then those (statistical) parameter estimates from the climate models as well as those from observations cannot be drastically different.

Figure 4 shows an example of the results in Philbin and Jun (2015). The figure displays estimates for the so-called *smoothness* parameter (how smoothly each climate variable varies over space) and the cross-correlation (correlation between the temperature and precipitation value at a given location) for the climate models and observations considered. While some models agree with each other (and with the observations), some models are quite distinct from the others. Philbin and Jun (2015) report that statistical models predict surface temperature and precipitation data with less smoothness than the observational data for the tropics. The estimated spatial cross-correlations of these two climate variables are quite different for most climate models in the mid-latitudes.

Climate model interdependence

Another interesting but challenging issue for climate model intercomparison is the models’ *interdependence*. As Knutti et al. (2013) note, most models are strongly tied to their predecessors, and some also exchange ideas and codes with other models. As a result, climate models are not only correlated with each other, but also with the earlier generation. Here, we do not simply mean how similar the climate model outputs are. Rather, we are concerned with how similarly wrong the climate models are.

Nevertheless, the current practice of quantifying the uncertainty of projected climate change, using these “ensembles” of climate models (as in Figure 3), often assumes that these multiple climate models provide “independent” information about the future climate. This assumption of independence within climate model ensembles leads us to incorrectly assess the levels of uncertainty (i.e., overconfidence) of future climate projections. For instance, even if 20 climate models are considered in a study, you will not get 20 sets of independent information but rather a smaller amount of information due to their dependence, i.e., their similarities.

However, it is not straightforward to define and quantify model interdependence for a given pair of climate models. For any given pair of climate models, how dependent (or similar) they are may be different for each climate variable, spatial region, and/or time period considered.

One notable work for understanding model interdependence is the “family tree” approach to climate models in Knutti et al. (2013; see Figure 5). The concept of a family tree is easy to understand, although, as seen in Figure 5, the tree structure is quite complex in this case. As might be expected, most climate models developed by the same institution are related at low levels of the family tree.

In a more statistical sense, Jun et al. (2008) quantified the dependence of a given pair of climate model errors using CMIP3 data. They considered 19 climate models from the CMIP3 archive. They found that there are only about 5 *degrees of freedom* in those 19 climate models (in other words, the information provided by the 19 climate models is ultimately equivalent to the amount of information that could be provided by 5 independent climate models!). Their study considered only the surface temperature variable as seasonal averages over 3 decades. Their conclusion might change if another climate variable or a different time scale (e.g., yearly average or monthly average) is considered.

Even if we can identify the actual degrees of freedom in an ensemble of climate models, it is not clear how we can incorporate this information into our study on climate change. It is not the case that we can simply identify 5 independent climate models among all the climate models considered. Instead, it is more likely that there are 5 linear combinations of all the climate models that are somehow independent of each other. Furthermore, if there is a particular climate model that is seriously wrong and has completely different outputs from the rest of the climate models, it could be mistakenly viewed as a valid, independent model (thus adding one degree of freedom to the entire pool of climate models). However, it would most likely not be useful (but actually harmful) for the study on climate change.

Concluding Remarks

Now that CMIP6 is under way (see Eyring et al., 2016), scientists and statisticians are excited about seeing greater improvement in climate models over their predecessors and, at the same time, face challenges that the new model archive will bring regarding model intercomparison. New models will be much more complex with more physical processes and parametrizations. They will use much finer grid resolutions (thus much bigger data!). Also

there will simply be much more climate models. The combination of excitement and challenges that must be confronted will never end, but it will surely bring us a better understanding of the future climate and the human influence on climate change.

Further reading

1. Eyring Veronika, Bony Sandrine, Meehl Gerald A., Senior Catherine A., Stevens Bjorn, Stouffer Ronald J., and Taylor Karl E. (2016), Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev*, 9, 1937–1958.
2. Jun Mikyoung, Knutti Reto, and Nychka Douglas W. (2008), Spatial Analysis to Quantify Numerical Model Bias and Dependence: How Many Climate Models Are There?, *Journal of the American Statistical Association*, 103, 934–947.
3. Knutti Reto, Masson David, and Gettelman Andrew (2013), Climate model genealogy: Generation CMIP5 and how we got there, *Geophysical Research Letters*, 40, 1194–1199.
4. knutti Reto and Sedlacek Jan (2012), Robustness and uncertainties in the new CMIP5 climate model projections, *Nature Climate Change*, DOI: 10.1038/NCLIMATE1716.
5. Philbin Robert, Jun Mikyoung (2015), Bivariate spatial analysis of temperature and precipitation from general circulation models and observations, *Advances in Statistical Climatology, Meteorology and Oceanography*, 1, 29–44.

Figure 1:
Schematic view of a global atmospheric and ocean model (source: NOAA).

Figure 2:
Comparison of grids for a) a global climate model and b) a regional climate model b) shows the increased grid in both horizontal and vertical dimensions (source: IPCC AR5)

Figure 3:

Multi-model means of surface warming (relative to 1980–1999) for the emission scenarios A1B, A2, and B1, shown as continuations of the 20th century simulation. This figure is based on CMIP3 runs. Six emission scenarios were considered, including the three in the figure. Scenario A1 represents an integrated world (rapid economic growth, globalization), and A1B is a subset of the A1 family that represents a balanced emphasis on all energy sources. Scenario A2 represents a more divided world with regionalization based on economic focus. Scenario B1 represents a more integrated and ecologically friendly world. More details on all scenarios can be found on the IPCC emissions scenarios website (source: IPCC AR4; <http://www.ipcc.ch/ipccreports/sres/emission/index.php?idp=3>).

Figure 4:

Climate model intercomparison results from Philbin and Jun (2015). The top row compares the smoothness of the temperature, the middle row the smoothness of precipitation, and the bottom row the cross-correlations for different regions of the Earth. The left column shows boreal summer and the right boreal winter. Colors represent modeling groups as shown in the legend in 4(a).

Figure 5:

(a) The model “family tree” from CMIP3 and CMIP5 (the latter marked with asterisks). A “distance matrix” for the temperature and precipitation fields was used to determine the dendrogram. (b) Same as (a), except that distance is calculated based on the predicted change in temperature and precipitation for the end of the 21st century. Here, the control state refers to the emission scenario with no external forcing, and rcp8.5 refers to the emission scenario with high greenhouse gas emissions. Each climate model is represented by its official CMIP model name, a combination of the institutional id and its model name (e.g. IPSL (Institut Pierre-Simon Laplace)-CM4 (name of one of IPSL’s models)) (source: Knutti et al., 2013).