Editorial: New Techniques for Improving Climate Models, Predictions and Projections

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Editorial on the Research Topic

New Techniques for Improving Climate Models, Predictions and Projections

INTRODUCTION

Complex climate models are the main tools used to make climate predictions and projections. Despite decades of development, models are still imperfect and generations of models have shown persistent mean-state biases such as the "double intertropical convergence zone (ITCZ)." Model imperfections lead to drift and errors in near-term initialized climate prediction systems and uncertainties in long-term future projections. Techniques such as bias correction and drift removal have been developed to reduce the impact of model imperfection in the case of predictions. Techniques such as emergent constraints and model selection have been used in projection studies. Are these techniques adequate, could they be improved upon, or should the community be investing their efforts into significantly improving the performance of climate models? Will higher resolution bring greater accuracy? Are there new techniques which can significantly improve climate predictions and projections?

The goal of this Research Topic was to explore new techniques for improving climate models, climate predictions, and climate projections. The 11 articles that are appearing in this special issue of Frontiers in Climate Predictions and Projections have together shown new avenues in improving the forecasts and projections, and introduce us to new science and new forecast products.

DATA AND DATA ASSIMILATION

A major topic in data assimilation is the reduction of the drift of the model away from the estimated observed state of the system. Volpi et al. introduce an innovative initialization technique to reduce the initial drift through a quantile matching between the observed state at the initialization time, and the model state distribution. The adjusted initial state pertains to the model attractor. Volpi et al. find added value of the quantile matching initialization in the North Atlantic subpolar region and over the North Pacific surface temperature as well as for the ocean heat content up to 5 years, and improved predictive skill of the Atlantic Meridional Overturning Circulation and the barotropic stream function in the Labrador Sea throughout the 5 forecast years.

In satellite-based wind retrievals, accuracy is impaired due to noise, while the maximal observable resolution is bounded by the often sparse distribution of sensors. Schweri et al. applying a neural network from numerical simulations on synthetic data show that data recovery at high resolution and high quality can be learned from simulation of physically realizable fluid flows. The study indicates that the learning-based reconstruction is especially powerful in handling large areas of missing or occluded data, relative to traditional models for data recovery. The authors demonstrate the usefulness of the method a real-world flow data set retrieved from satellite imagery of stratocumulus clouds on Guadalupe Island.

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (AI/ML) APPROACHES

Serifi et al. explore the capabilities of neural networks to reconstruct high-resolution data from low-resolution weather simulations and observations datasets. They investigate supervised machine learning using multiple deep convolutional neural network architectures to test the limits of data reconstruction for various spatial and temporal resolutions, low-frequent and high-frequent input data, and the generalization to numerical and observed data. Climate data produced by the COSMO regional climate model at 2.2 km during 2 months of 2008, and observations from Switzerland in 2004 at 1 km are used. While slowly-changing information, such as temperature can be adequately predicted through an error-predicting network, these networks are far less suitable than deconvolutional neural networks for the analysis of high-frequent fields like precipitation due to poor learning performance.

AI/ML techniques also feature in Mitra who uses a probabilistic graphical model, capable of a binary representation, to identify the spatial distribution in the simulated daily rainfall over the Indian landmass during monsoon in several Coupled Model Intercomparison Project Phase 6 (CMIP6) models, and compares the patterns with those from the observed rainfall for the 2000–2014 period. The study suggests that some of the CMIP6 models simulate the spatial distribution of monsoon rainfall to a reasonable degree, but most models underestimate extreme rainfall events, and are unable to reproduce the homogeneity in rainfall across various regions of the landmass, as observed.

CLIMATE PREDICTABILITY AND PREDICTIONS

Looking at the predictability of the climate system, Ikuyajolu et al. employ a computationally fast method to look at the potential predictability of sea surface temperatures in the tropical Pacific and Indian Oceans during boreal fall. The predictability of the basins is controlled by two regularly varying non-linear oscillations, the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). Using historical and RCP8.5 outputs from several CMIP5 models and reanalysis data, the authors do not find robust changes in predictability in future projections, despite the discrepancies between the models and the reanalysis. A brief investigation of the discrepancy in predictability in the basin points to a poor representation of the ocean mean state and inter-basin connectivity at the Indonesian Throughflow.

Also focussing on the predictability of climate variability, Sahai et al. present the newest version of the India Meteorological Department multi-physics multi-model ensemble extended range prediction system. While this system includes older options of coupled climate forecast system version 2 and atmospheric global forecast system forced with real-time bias-corrected sea-surface temperature from NCEP coupled forecast system model version 2, unlike the predecessor, the horizontal resolution is "seamless," i.e., the model forecasts are generated at T574 resolution till 15 days, after which, a coarser T382 resolution is selected. In the newer version, model integrations are performed six times in a month for real-time prediction. Analysis of the 15 year-hindcast generated demonstrate appreciable improvements over its predecessor in predicting the large-scale low variability signal and weekly mean rainfall up to 3 weeks lead, and importantly, better performance at subdivisional scales, especially in the northwest and central parts of India.

On longer time scales, Feba et al. highlight considerable advancement in the multi-year prediction and show, for the first time, that decadal predictions from two general circulation models have significant prediction skills for the IOD for at least 2 years and up to 8–10 years after initialization. This skill is present despite ENSO having a lead prediction skill of only 1 year. The source of this multi-year predictability lies in sub-surface signals that propagate from the Southern Ocean into the Indian Ocean. Prediction skill for a prominent climate driver like the IOD has wide-ranging benefits for climate science and society.

Using the technique of event coincidence analysis, Weidermann et al. decipher differential imprints of the East Pacific (EP) and Central Pacific (CP)/Modoki flavors of ENSOs on very low and very high seasonal precipitation patterns over distinct regions across the globe. The authors find that EP periods exhibit statistically significant event coincidence rates with hydrometeorological anomalies at larger spatial scales, whereas sparser patterns emerge along with CP periods. The study documents, for the first time, distinct impacts such as increased rainfall over Central Asia during CP periods. The authors argue for a thorough distinction of El Niño and La Niña into their two respective flavors for understanding the emergence of strong regional hydrometeorological anomalies and anticipating their associated ecological and socioeconomic impacts.

CLIMATE PROJECTIONS AND UNCERTAINTIES

Clouds are important for feedbacks in the climate system, yet their representation leads to considerable uncertainty in model projections of climate change. Pathak et al. introduce an efficient uncertainty quantification and Bayesian inference for cloud parameters in order to assess the sensitivity of the outputs of the NCAR Single Column Atmosphere Model to various

parameterization schemes. The method involves using two surrogate models that propagate uncertainty in test parameters to model outputs. Their exercise, for example, shows that ~40–80% of the total variance of the climate variables can be attributed to auto-conversion size threshold for ice to snow, ~15–30% to the fall speed parameter for stratiform cloud ice, and so on. The study is valuable in quantifying the source of uncertainties in the model physics.

Feedbacks between climate and the carbon cycle also represent a major uncertainty in projections. Using a simple carbon cycle model, and driving emulators of the temperature responses of 41 Coupled CMIP6 emulators with 127 different emission scenarios for the 21st century, Rypdal et al. find almost a perfect linear relationship between maximum global surface air temperature and cumulative carbon emissions, allowing unambiguous estimates of Remaining Carbon Budget (RCB) for each CMIP6 model. The range of these estimates across the model ensemble provides a measure of the uncertainty in the RCB arising from the range in climate sensitivity over this ensemble. Rypdal et al. suggest that observational constraints imposed on the transient climate response in the model ensemble can reduce uncertainty in RCB estimate. They also show that main uncertainty of the transient climate response to cumulative carbon emissions and the associated RCB is not due to the spread of the emission scenarios, but rather the spread of sensitivities over the CMIP6 model ensemble.

Uncertainties may be reduced by the application of constraints on projections. The paper by Hegerl et al. discusses the challenges in understanding the role of observations in skill estimates and constraints, and using them consistently in predicting and projecting changes in European climate. It discusses constraints across prediction and projection methods, their interpretation, and the metrics that drive them. These are illustrated in this paper by examples of state-of-the-art methods for predicting and projecting changes in European climate. The authors study how the skill estimates may vary over time for initialized predictions with different phases of climate variability and climatic conditions, and are influenced by the presence of external forcing. This, the authors state, complicates the systematic use of observational constraints. They also suggest that sub-selecting simulations from large ensembles based on reproduction of the observed evolution of climate variations is a good testbed for combining projections and predictions.

Improving climate predictions and projections is such a big subject area within climate science that this Research Topic could not cover all potential ways in which advances can be made. Nevertheless, some interesting themes emerge. Blending models with observations on climate time scales, and the use of Artificial Intelligence and Machine Learning techniques, are proposed routes for the creation of so-called "digital twins" of the climate system. Such tools are intended to be more powerful than our current models and can be better focussed on policy questions. However, there is still much to be learnt about what is predictable in the near term and how we can quantify and reduce uncertainties in projections of long-term climate change, these efforts are required even if efforts to limit the size of climate change succeed, as there is already a requirement for societies to adapt.

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