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Stochastic Modeling of Temperature Extremes over continental United States and Canada

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JpGU–AGU Joint Meeting 2017

Session: M-GI29: Data-Driven Analysis, Modeling and Prediction in Geosciences; Presentation number: MGI29-P14; Display time: Saturday, 20 May 2017, 03:30-5:00PM

Introduction

State-of-the-art numerical weather prediction models are expensive to run and are subject to biases due to imperfect physical parameterizations of unresolved processes. An alternative strategy for weather and climate prediction builds on extremely numerically efficient empirical stochastic models, which have recently been shown to be able to capture detailed statistics of select climatic fields of interest (Kravtsov et al. 2016). In this work, we apply this technique to obtain ensemble simulations of surface atmospheric temperature (SAT) over North America; these simulations can be used, among other things, to estimate long-term changes in the spatial distribution and magnitude of extreme heat waves and cold spells in the region.

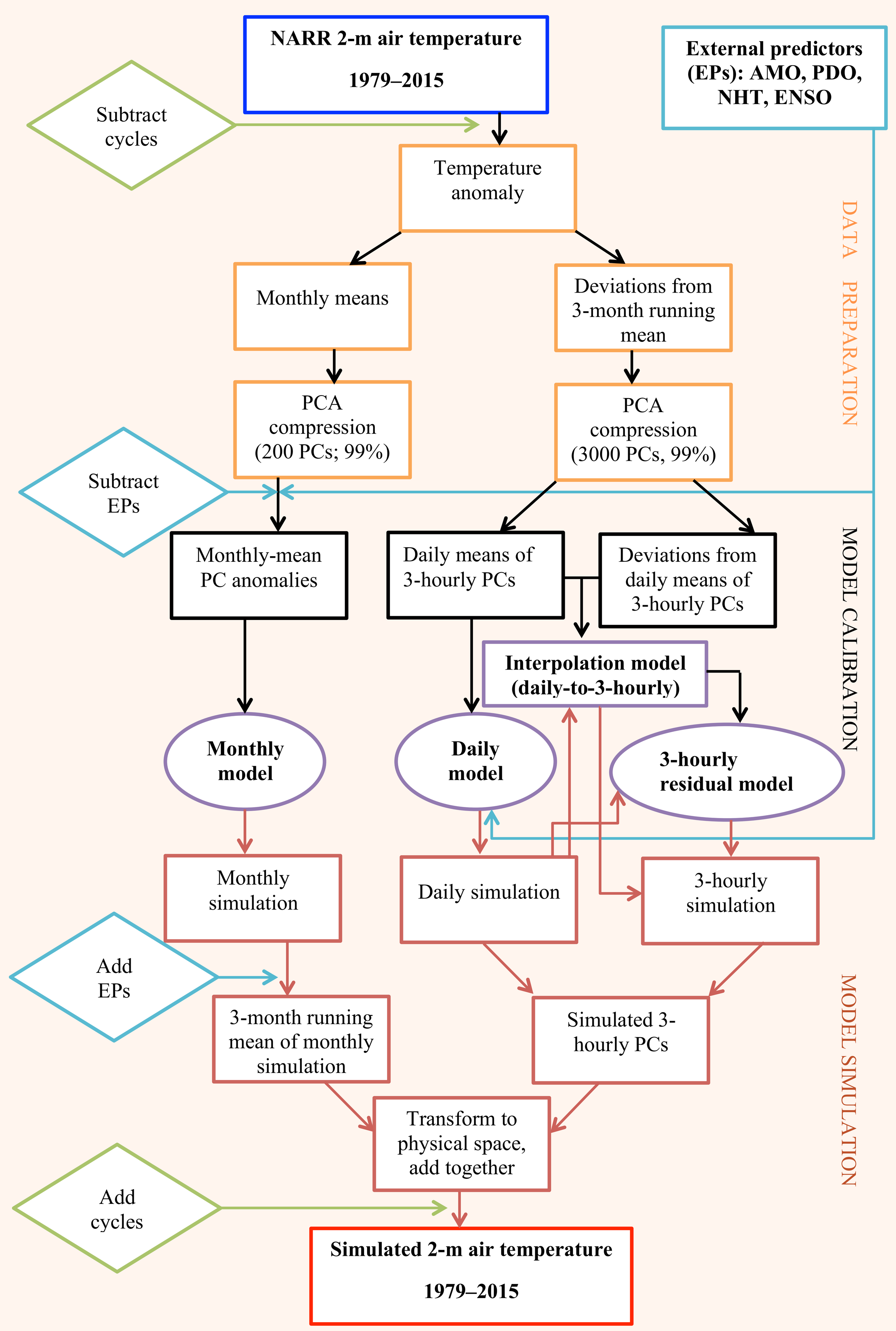

Fig. 1: Empirical model construction and air-temperature simulation flowchart. The three-tier empirical model is based on the North American Regional Reanalysis (NARR) 2-m air temperature data and is conditioned on external predictors (EPs) that describe climate variations associated with large-scale climate modes.

Input data sets and methodology

We used surface temperature data set based on NCEP North American Regional Reanalysis (http://www.esrl.noaa.gov/psd/data/gridded/data.narr.html): NARR. The NARR data set is comprised of 3-hourly "observations" on a 349×277 grid with nominal spatial res-olution of 32 km, over the 1979–2015 period; about a third of these data are from locations within North America; the resulting data thus has a dimension of ~100000×30000. We subtracted from raw temperature data its seasonal climatology, and built our model in the phase space of surface temperature EOFs (Monahan et al. 2009), to account for over 99% of the total variability. The model's building block is a stochastic ARMA model for the principal components **x**, postulated to have the following multi-level form (Kravtsov et al. 2005) [$d\mathbf{x}=\mathbf{x}^{n+1}-\mathbf{x}^{n}$]:

$$d\mathbf{x} = \mathbf{x} \cdot \mathbf{A}^{(1)} + \mathbf{r}^{(1)},$$

$$d\mathbf{r}^{(1)} = [\mathbf{r}^{(1)}\,\mathbf{x}] \cdot \mathbf{A}^{(2)} + \mathbf{r}^{(2)}, \qquad (1)$$

$$d\mathbf{r}^{(2)} = [\mathbf{r}^{(2)}\,\mathbf{r}^{(1)}\,\mathbf{x}] \cdot \mathbf{A}^{(3)} + \mathbf{r}^{(3)},$$

where the model's parameters are found via regularized multiple linear regression and depend on seasonal cycle at monthly resolution. The model (1) was estimated separately for temperature time series at monthly, daily (for deviations from 3-month means) and three-hourly (for deviations from daily means) resolutions (**Fig. 1**). Input monthly data for the model were obtained by regressing out linear dependence of temperature on external predictors: mean NH temperature, AMO, PDO and Nino3.4 indices. At the stage of simulation, the model was driven by state-dependent noise, whose amplitude was also a function of external predictors. The simulated PCs were transformed back to physical space, with externally forced signal and seasonal climatology added, to provide an emulation of observed variability.

Model performance

We first analyzed a single 1979–2015 simulation of the empirical model run from random initial conditions, which produces a synthetic time series of surface temperature on the NARR spatiotemporal grid. This simulation is by construction uncorrelated with the observed data, except for, perhaps, forced signals associated with external predictors.

The model reproduces well the seasonal cycle of temperature variance (not shown). The largest discrepancy between the model simulated and observed variance occurs during the cold DJF season (**Figs. 2a–c**), where the model, while capturing very well the spatial pattern of the variability, somewhat underestimates the magnitude of this variability over northwestern and central North America, primarily due to overly diffusive (in space) cold polar air intrusions from the Arctic plains (not shown; a hint of this behavior can be seen in **a Supplemental Movie**). These biases can be corrected via quantile mapping of the simulated local distributions onto the observed distributions, for each synthetic simulation.

One of the major advantages of the empirical model considered here is that it is able to capture complex spatiotemporal relationships between the features of the temperature variability associated with forced and internal atmospheric dynamics. **Figure 3** shows examples of anomalous seasonal cold (top two rows) and warm conditions (bottom row). Note that the persistent cold-spell events we have chosen happen in different years in observations and model simulations, which means that they likely stem from the internal dynamics — and are tentatively due to enhanced frequency of synoptic events causing cold-air outbreaks in the months considered. On the other hand, the July 2012 anomalously warm conditions over US Great Plains happen both in observations and in the model simulations, suggesting that this pattern is externally forced (cf. Hoerling et al. 2014; McKinnon et al. 2016).

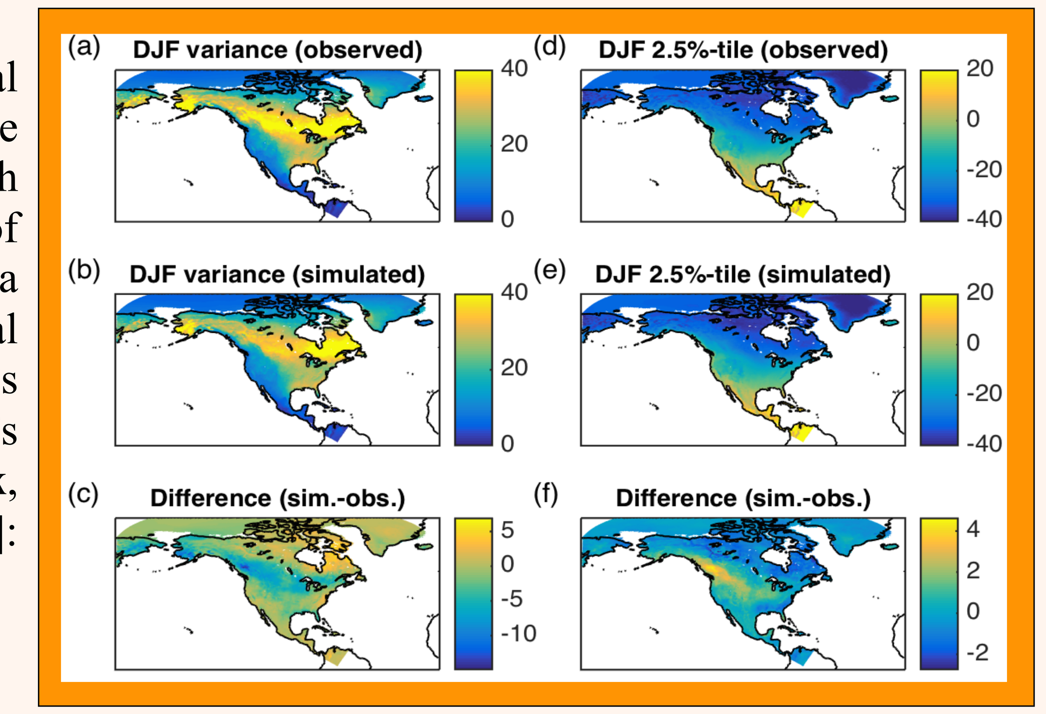

Fig. 2: Observed (top) and simulated (middle) three-hourly SAT statistics (1979–2015), with the difference displayed in the bottom panel. Shown are the 37-yr mean of SAT's DJF variance (left) and 2.5%-tile (right) for each year.

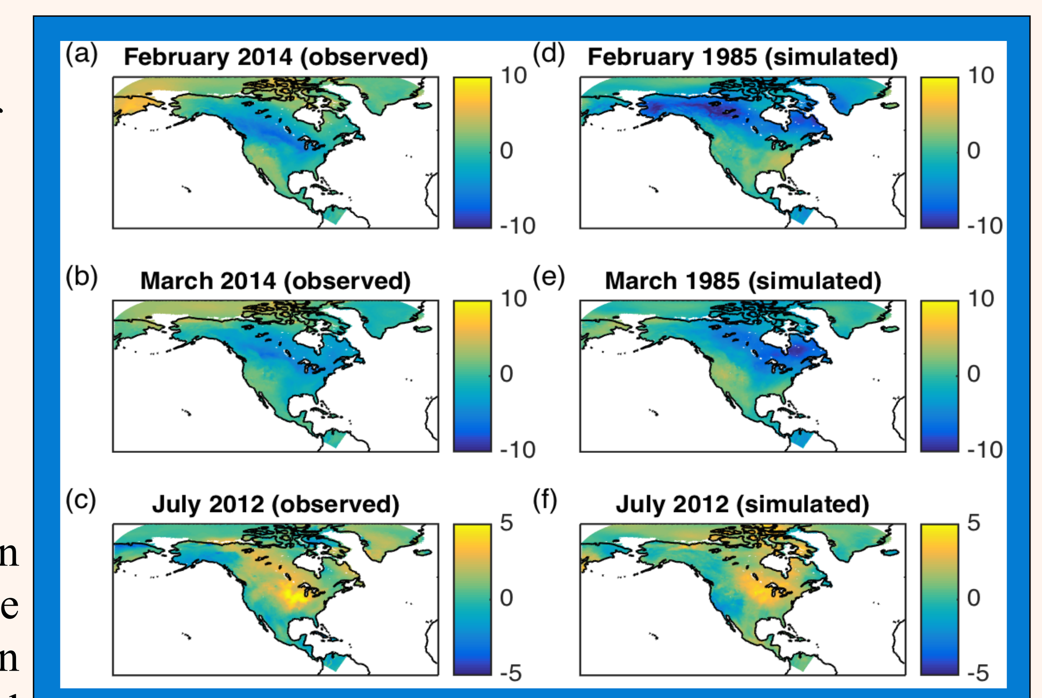

Fig. 3: Examples of monthly SAT from observations (left) and empirical model simulations (right). The first two rows show a persistent JFM cold spell; the bottom row exemplifies summertime drought conditions.

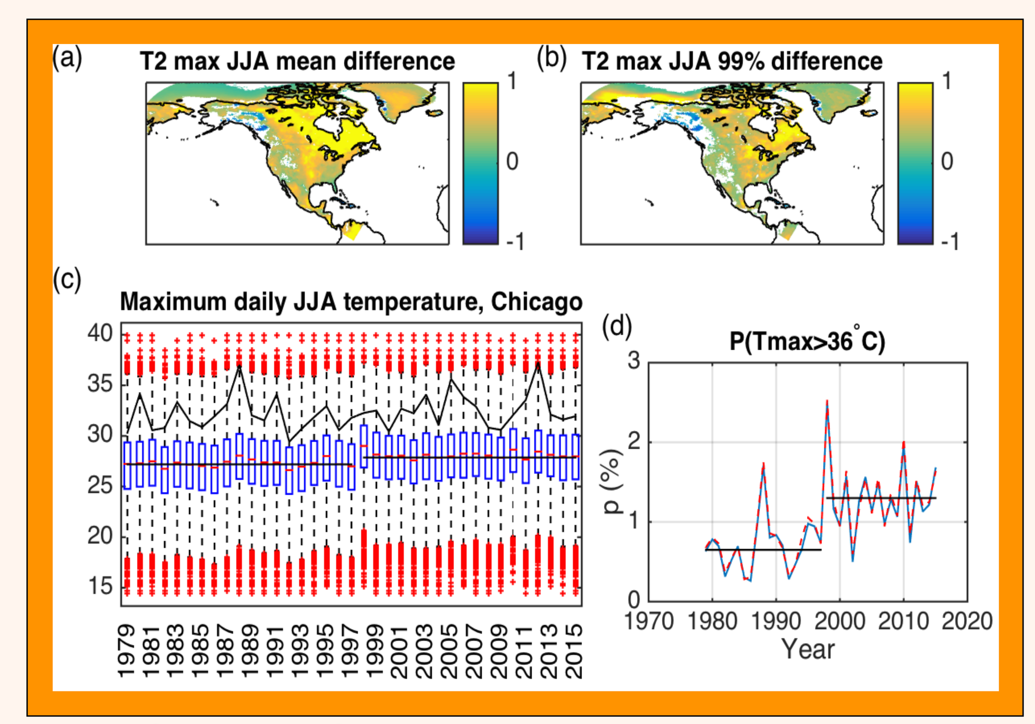

Fig. 4: Simulated SAT distributions evolve due to the model dependence on external predictors. (a, b) show difference maps between JJA distributions for 1979–1997 and 1998–2015 periods. (c, d) analyze the simulated time series near Chicago O'Hare airport location.

Library of climate simulations

A key advantage of the empirical stochastic model developed here, aside from its excellent performance in reproducing diverse statistical characteristics of the observed surface temperature variability, is its extreme computational efficiency. We performed 100 simulations of SAT over the entire 1979–2015 period, and created a library that documented the simulated daily minimum and maximum temperatures for both the raw output and the output quantile mapped to observations.

These simulations provide various types of probabilistic information that cannot be obtained based on the direct statistical analysis of the observational record, which demonstrates the essential utility of our proposed empirical modeling methodology (see examples in **Fig. 4**). Needless to say that completing similar tasks using the high-resolution dynamical models (that is, numerical models based on first physical principles and state-of-the-art parameterizations of unresolved processes) is still computationally prohibitive.

The resulting data set provides unique opportunities for the analysis of weather-related risk, with applications in agriculture, energy development, and protection of human life.

References

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Acknowledgments

This research was supported by the Society of Actuaries' Climate Change and Environmental Sustainability Research Committee. SK was also funded by the NSF grants OCE-1243158 and AGS-1408897.

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