Multi-Scale Empirical Modeling of Atmospheric Variability

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Project goals and specific objectives

Climate is extremely complex. Identification, as well as attribution of climate signals may be ambiguous. One way of approaching this problem is by concentrating on a subset of large-scale low-frequency climate modes and determining their reproducibility by climate models and, eventually, their predictability. The **major goals** of this collaborative project (#1243175 UCLA, PI: Dr. D. Kondrashov and #124158, PI: Dr. S Kravtsov) are (i) to identify potentially predictable low-frequency modes (LFM), where "low-frequency," in climatic perspective, refers to interannual-to-decadal and longer time scales; and (ii) develop means for effective empirical modeling of these modes on global-to-regional scales, as well as of their interaction with smaller-scale, faster processes.

The LFM we studied included ENSO-type variability and decadal-to-multidecadal climate variability throughout the Northern Hemisphere, in particular the inherently global modes that result from the interaction between these LFM subcomponents (Wyatt et al. 2012; Kravtsov et al. 2014b, 2015). These diagnostic studies highlighted, in particular, an intriguing relationship between LFMs and atmospheric synoptic eddies (Kravtsov and Gulev 2013; Kravtsov et al. 2014a). This led to an idea of comprehensive empirical modeling of atmospheric and climate variability throughout the entire range of spatial and time scales. One of the **major specific objectives** of the past year was to test the capability of the Empirical Model Reduction technique (Kravtsov et al. 2005) in faithfully representing the atmospheric variability across the whole spatiotemporal landscape, from synoptic scales to hemispheric and global LFMs.

Methodology

We have developed an empirical stochastic model capable of emulating and predicting evolution of the sea-level pressure (SLP). The model was trained on the 6-hourly, 0.75º resolution Northern Hemisphere's SLP data from the 1979–2013 ERA-Interim Reanalysis (Dee et al. 2011).

The process of model construction involves several steps **(Fig. 1)**. First, we subtract from the full data the monthly SLP climatology and form daily-mean SLPA anomalies. Next, the resulting daily SLPA anomalies are projected onto its 1000 leading Empirical Orthogonal Functions (EOFs: Monahan et al. 2009), which account for over 99% of the total SLPA variability. The stochastic ARMA model for the SLPA principal components **x** is postulated to have the following multi-level form (Kravtsov et al. 2005) [d**x**=**x**$^{n+1}$– **x**^{n}]:

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

the model's parameters are found via regularized multiple linear regression and depend on seasonal cycle at monthly resolution.

At the stage of model simulation, the residual forcing at the third model level $\mathbf{r}^{(3)}$ is chosen via random sampling from the library of the observed residuals in a way conditioned on the simulated state **x**. The simulated daily anomalies are also used to model, empirically, the 6-hourly SLPA residuals. The resulting 6-hourly SLPA anomalies are transformed back to physical space and, after adding the mean seasonal cycle, represent an emulation of the full SLP time series.

It should be noted that our empirical model is not expected to produce climate realizations pathwise similar to the observed climate; on the contrary, the climate simulated by such a model would be, by construction, statistically independent of the actual observed climate realization. Hence, we should judge the success of the model's performance by comparing not the pathwise convergence, but rather the long-term statistical properties of the observed and simulated SLP variability, such as the spatiotemporal SLP spectra or the composite characteristics of the individual cyclones within storm tracks.

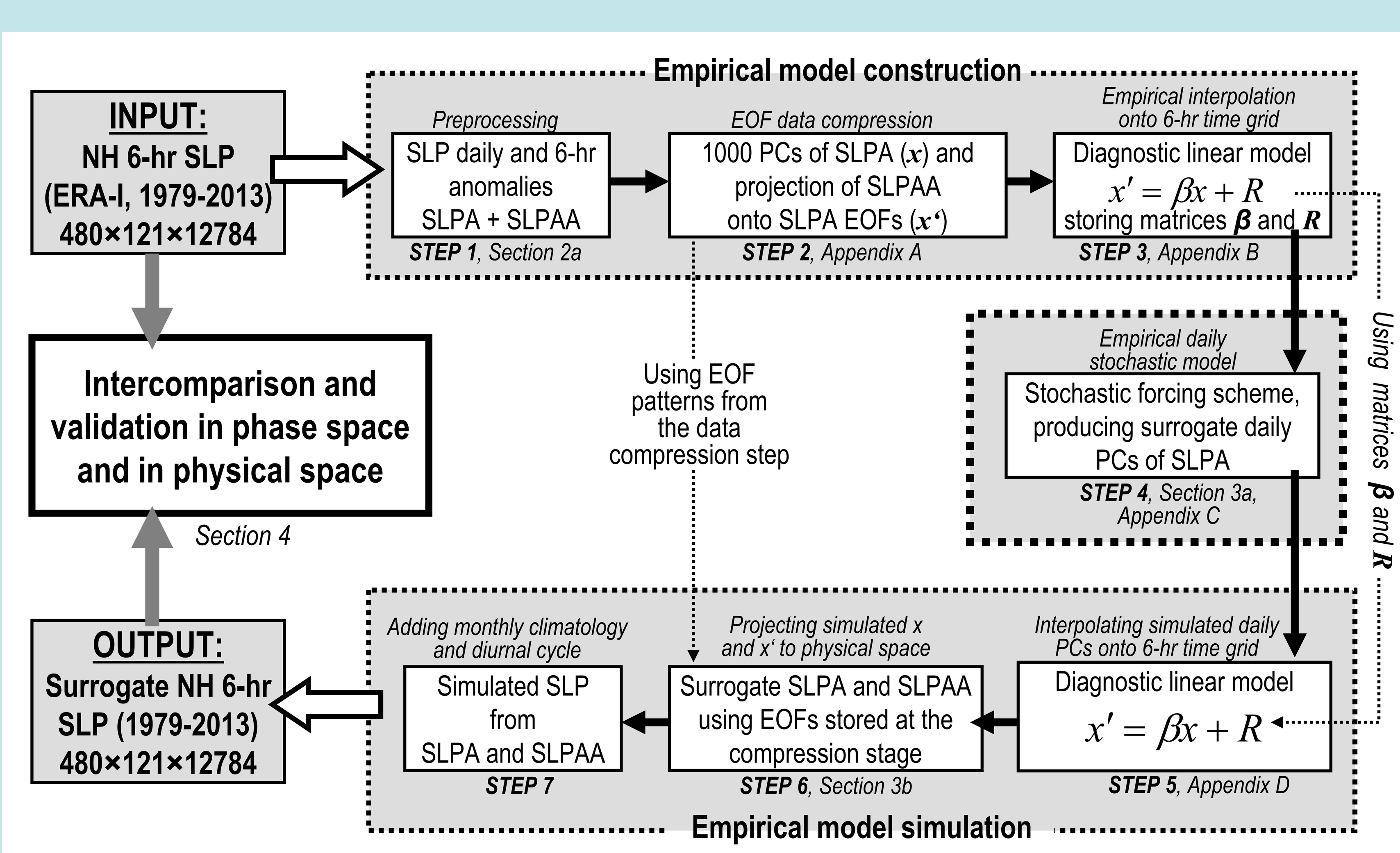

Figure 1: The flowchart of the empirical model construction and validation procedure.

Results

As an illustration of our empirical model performance, we show in Fig. 2 how well this models captures both the observed magnitude and patterns, as well as the seasonal cycle of **the band-pass filtered SLP variance**. In Fig. 2 (right column), the differences between the observed and simulated variance are not statistically significant. Similar impressive matches (not shown here) exist between the observed and simulated statistics of propagating SLP anomalies, identified via various Eulerian and Lagrangian methods. In particular, the model reproduces, statistically, diverse characteristics of the cyclone tracks (Rudeva and Gulev 2007), such as cyclone spatial and the probability distributions of various cyclone properties throughout their life cycles.

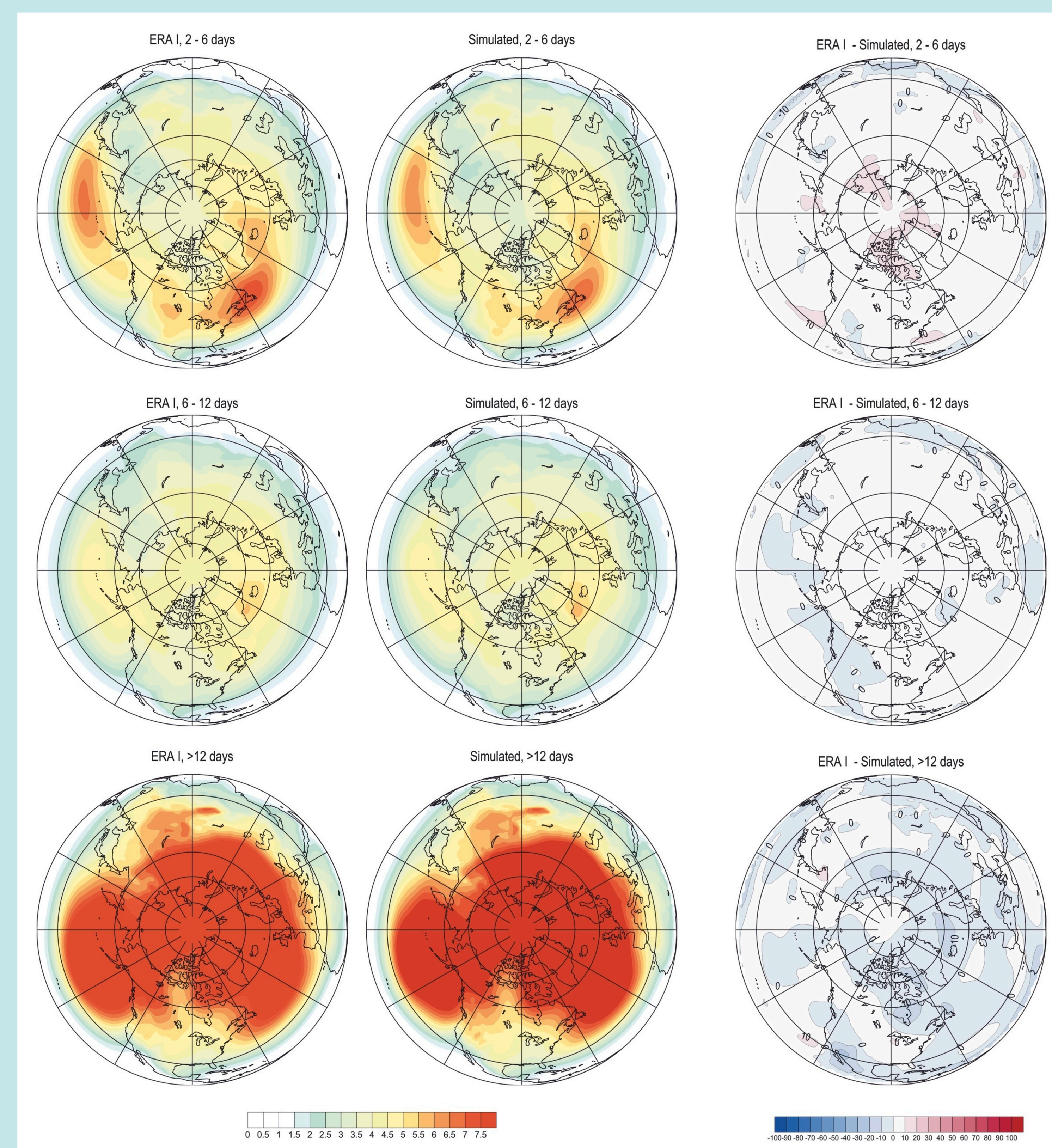

Figure 2: Standard deviations (hPa) of the wintertime (JFM) observed (left column) and simulated (middle column) band-pass filtered SLPA anomalies in physical space; the relative difference (observed – simulated) in % is shown in the right column. The three rows (top to bottom) correspond to the 2–6-day and 6–12-day band-pass filtered, and 12-day low-pass filtered anomalies, respectively.

Discussion and future work

Building on decades of our previous work on empirical modeling of climate, we have constructed examples of highly efficient and statistically accurate EMR models able to capture the entire complexity of climate variability in selected fields of interest: thus far, sea-level pressure (SLP) [Kravtsov et al. 2015 and multi-level vector winds [not shown]. The model construction and simulation methodology brings together in a unique fashion numerous elements of the state-of-the-art empirical data modeling, including a generalized regularized method of constructing optimal linear inverse models (LIMs), parameterizations of the nonlinear interactions via multiplicative noise, past-noise forecasting usage of the observed noise snippets conditioned on the large-scale state of the system considered, as well as highly accurate statistical interpolation of the simulated fields to a higher temporal resolution. The emulated climatic fields have a wide spectrum of potential applications in climate variability diagnosis/identification, error estimation and statistical prediction studies. In particular, we further plan to use the SST-dependent vector-wind emulator as the atmospheric component of an extremely numerically efficient, truly multi-scale hybrid coupled model deploying either empirical or dynamical oceanic component

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