State-Space Analysis of Model Error: A Probabilistic Parameter Estimation Framework With Spatial Analysis Of Variance

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LONG-TERM GOALS

An over-arching goal in prediction science is to objectively improve numerical models of nature. Meeting that goal requires objective quantification of deficiencies in our models. The structural differences between a numerical model and a true system are difficult to ascertain in the presence of multiple sources of error. Numerical weather prediction (NWP) is subject to temporally and spatially varying error, resulting from both imperfect atmospheric models and the chaotic growth of initial-condition (IC) error. The aim of our work is to provide new methods that begin to systematically disentangle the model inadequacy signal from the initial condition error signal.

OBJECTIVES

We are engaging a comprehensive effort that uses state-of-the-science estimation methods in data assimilation (DA) and statistical modeling, including: (1) the characterization of existing model-to-model differences via heirarchical spatial modeling methods; (2) the development of a flexible representation for the various spatial and temporal scales of model error; (3) the estimation of parameters to represent those scales using a probabilistic approach to DA, namely the Ensemble Kalman Filter; and (4) the determination of whether incorporation of estimated error structure in improves short-term forecasts, again using heirarchical methods, this time within a formal testing framework. Research focus is on near-surface winds over both the ocean and land. The method under development are sufficiently general and can apply to a wide range of battlespace environments.

APPROACH

The technical approach includes numerical weather prediction and state estimation efforts at NPS, and statistical modeling efforts at University of California Berkeley (UCB) under sub-contract. At NPS PI Hacker and post-doc Kolczynski are implementing the Navy's Operational Global Atmospheric Prediction (NOGAPS), and two limited-area mesoscale models: the Navy's Coupled Ocean-Atmosphere Mesoscale Prediction System (COAMPS) model, and the open-source Weather Research and Forecast (WRF) model, within a state-of-the-science ensemble Data Assimilation Research Testbed (DART). The NOGAPS-DART provides global ensemble prediction capability that can be consistently applied to the COAMPS and WRF as lateral boundary conditions. Scientific objectives will be met by systematically choosing the WRF or COAMPS as the "truth," which can provide observations for assimilating into the other model. Under this approach, spatio-temporal distributions of uncertainty (error in this context) are available for analysis with special attention to second-order moments. Eventually, we will use the same framework to objectively estimate parameters in statistical models, of NWP model error, developed at UCB. Hypotheses are being formed and formally tested.

UCB PI Cari Kaufman is working to advance the statistical methods needed to provide an objective space-time characterization of the error distributions. Uncertainty is characterized via fitting a hierarchical Bayesian model that captures the important features and variability in the data. The implied distribution from the model will be a valid stochastic spatial process under probability theory. Ideally, fitting the statistical model to different datasets should allow us to capture the significant differences between the different underlying data generating distributions. Moreover, a realistic statistical model can also simulate realistic wind fields quickly which can be beneficial for studying other processes that require surface winds as an input. Graduate student Wayne Lee (unfunded) is contributing substantially to this work. Postdoc Benjamin Shaby began work in September 2011 and completed his appointment in Feb. 2013.

WORK COMPLETED

Continued funding lags led to a significant reallocation of resources toward different tasks in FY2013. Work focused on the most promising aspects of earlier work, and leveraged other related projects. Tasks requiring ambitious technical development work prior to scientific discovery were abandoned. No significant work was wasted, and instead the technical development through FY2013 were leveraged to obtain meaningful results. The result was a focus on Tasks 4 and 5, with modified technical details underlying each.

At NPS, analysis of the WRF-DART state estimates and predictions, driven from NOGAPS-DART and the radiosonde network during an Oct 2009 simulation period, continued with Self-Organizing Maps (SOMs) adapted to understand model errors. SOMs have emerged during the last decade, provide an objective method for classification, and have not been expanded to use in predictability and model inadequacy. Systematic increments reveal time- and space-dependent systematic errors, while SOMs provide a method for categorizing forecasts or increment patterns. The SOMs can be either used for direct analysis, or used to produce composites of other fields. This study uses the forecasts and increments of 2-m temperature and dry column mass perturbation (μ) over a four-week period to demonstrate the potential of this technique. Results demonstrate the potential of this technique for identifying spatially varying systematic model errors. Results from FY2013 are presented below. NPS also began work to extend the error estimation and parameter estimation experiments with the single-column version of the WRF model in DART, to 3-dimensional experiments.

At UCB focus was on addressing challenges associated with applying heirarchical Bayesian techniques to large, multivariate, and non-stationary datasets typical of NWP. Methods proposed and tested during FY12 were applied to real data in FY13. The first is incorporation of the geostrophic relationship into a hierarchical model to relate surface winds to pressure gradients, allowing the geostrophic coefficients to vary spatially, and the use of a Gaussian Markov random field (GMRF) approximation to speed computations. Results from application to 40 years of model data confirm that physical constraints, such as geostrophy, applied to a heirarchical model can help identify dependence structures. Second, a hierarchical Bayesian model explicitly separates error fields occurring at different time scales in sea-surface temperature fields, representing a more informative extension of empirical orthogonal functions (EOFs). With future work, we expect these methods to merge with work at NPS.

RESULTS

1. Mesoscale model results

Systematic increments from data assimilation are a linear function of model errors integrated over the assimilation interval. The challenge is to intepret the increments in space and time to reveal the scales of model errors. We have recently examined Self-Organizing Maps (SOMs; Kohonen, 1988) as a tool for identifying the coherent systematic error structures. SOMs are unattended machine-learning algorithms that produce low-dimensional “maps” of possible state vectors called “nodes” organized in a way so that nearby nodes are similar. The location of the nodes is specified and may be arranged in any pattern, though rectangular and hexagonal grids are most common. The method has been used for cluster analysis in the past, but not been used in a data assimilation context or to understand model inadequacy. We have applied SOMs to the ensemble-mean increment in meteorological fields produced by DART-NOGAPS-WRF.

SOMs are produced through an iterative process. During each iteration a random state is chosen from the training dataset. The random state is compared to each node to identify the node closest to the chosen state based on a cost function (often the root-mean-squared error). That node is adjusted closer to the random state. Nearby nodes are also adjusted closer to the same random state (to a lesser degree). The magnitude of the adjustment and the size of the neighborhood are both reduced with each iteration, so that initially large changes are made to a large portion of the map become small changes to individual nodes.

This particular study explored a technique for identifying model error using self-organizing maps (SOMs) and analysis increments. Because increments quantify the changes in the model state made by the assimilation system to more closely represent observations, they are a measure of the forecast error. The SOM wass used to categorize forecasts or increments, which can then be analyzed directly or used to make composites of other fields. SOMs objectively condition or classify the data set based on flow characteristics contained within a subset of the model state.

Here we focused primarily on two forecast variables: 2-m temperature and dry column mass perturbation (μ) over a roughly four-week period. SOMs produced using the forecasts of each exhibit readily identifiable patterns. The temperature forecast SOM primarily separated by time of day, presumably driven by diurnal heating. In contrast, the synoptically dominated μ forecast separated into multi-day periods reflecting the synoptic pattern.

Composites of analysis increments for each SOM demonstrate possible model and/or data assimilation deficiencies. Composite increments of μ for the temperature forecast SOM are generally negative, and are more negative for the colder SOM nodes. Composite increments of μ for the μ forecast SOM indicate a potential problem in the model system with ridge and trough formation over central North America. An example is given in Fig 1.

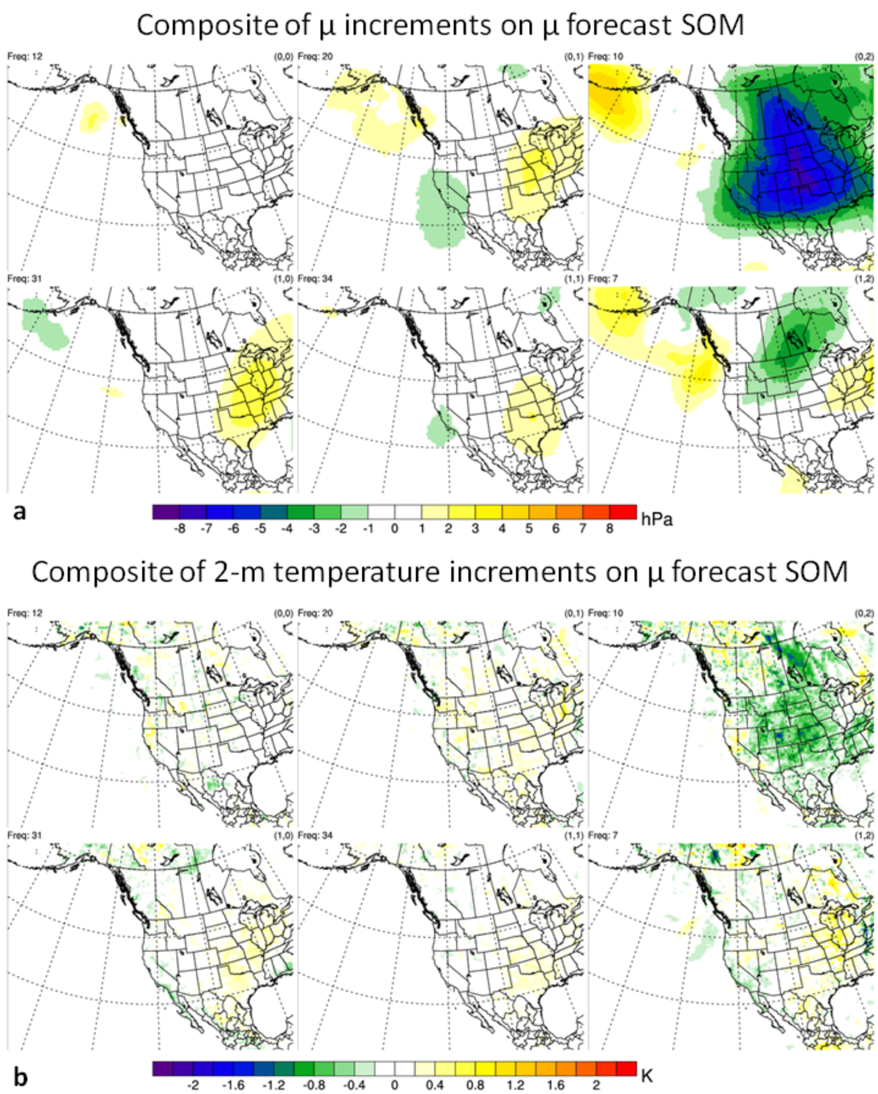

Fig. 1: Composites of (a) dry air mass (μ) increments and (b) 2-m temperature increments for the dry air mass (μ) forecast SOM. Frequency counts above each panel refer to the number of forecasts composited in each panel. The feature that stands out most in the μ increment composite for the μ forecast SOM (Fig. 1a) is the large negative increment over central North America in the composite for node (0,2). The μ forecast SOM for that node exhibits ridging over central North America, and the composite increment is strongly negative. The combination suggests that the model systematically over-amplifies the ridge in the lee of the Rockies.

This research represents only a preliminary examination of this method and there is much room for extension and augmentation. One possibility is to include additional information related to the ensemble distribution to the SOM. For instance, SOMs could model the mean and variance of an ensemble, adding forecast uncertainty to the analysis. Another possibility is the use of multi-variable SOMs, combining multiple variables into a single categorization of forecasts or increments. There are also the obvious extensions of the presented technique such as a longer analysis period, additional variables, and different SOM node configurations.

In a separate study leveraging other ongoing work, extended the parameter estimation work reported in Hacker and Angevine (2013) from a single column to 3D. Experiments with the single-column implementation of the WRF model provide a basis for deducing land-atmosphere coupling errors in the model. Coupling occurs both through heat and moisture fluxes through the land-atmosphere interface and roughness sub-layer, and turbulent heat, moisture, and momentum fluxes through the atmospheric surface layer. Thermal fluxes are directly affected by the aerodynamic roughness temperature, which is neither observable nor available from energy balance solutions at the surface of the earth. Often, a constant parameter determines the thermal roughness as a contant multiple of the momentum roughness length. Hacker and Angevine (2013) showed that state augmentation in ensemble data assimilation with a single column model both provide time-varying estimates of the parameter value, and also result in reduced systematic model error.

The Extension to 3D allows a spatial characterization of the parametric error controllong the turbulent fluxes. Results are forthcoming, but sensitivity tests performed by changing the domain-constant value of the parameter from 0.01 to 1.0 (a plausible range based on a literature review) show significant spatial variability. Given that forecast biases are often state dependent, we might expect significant variability in the parameter estimates.

2. Modeling Uncertainty in Surface Wind Fields

We continued our work to construct a probabilistic model to characterize the dependence structures in surface wind fields. In previous reports, we described our incorporation of the geostrophic relationship into a hierarchical model to relate surface winds to pressure gradients, allowing the geostrophic coefficients to vary spatially, and the use of a Gaussian Markov random field (GMRF) approximation to speed computations. Our work this year has been to demonstrate and evaluate our model using the Japanese Model MIROC3.2 at medium resolution under the pre-industrial experiment scenario. In this analysis, we work with average wind fields over each season for each year. This yields 40 years of average surface wind fields for winter and summer.

To illustrate these results, Figs. 2 and 3 show the posterior means for the spatially varying coefficients for the winter wind fields. One quick sanity check is the agreement with the geostrophic relationship. Given that the Coriolis force switches sign at the equator, the sign change for the geostrophic coefficient at the equator is promising. Another promising aspect is the fact that the geostrophic coefficients are larger in magnitude over the ocean than land. This confirms our understanding about the effect of friction on wind velocity. The coefficient process also shows a discontinuous behavior when the topography changes between land and sea, which is a feature we wanted to capture in this model. Another interesting fact is the ageostrophic pressure gradient is consistently negative if not zero.

Besides the agreement with the geostrophic effect, prediction accuracy is also useful to help evaluate models. Figure 4 shows the predicted wind velocities *vs.* the actual wind velocities in 10 years of data set aside for testing. Relative to the overall variability in the wind components, the prediction error is quite small.

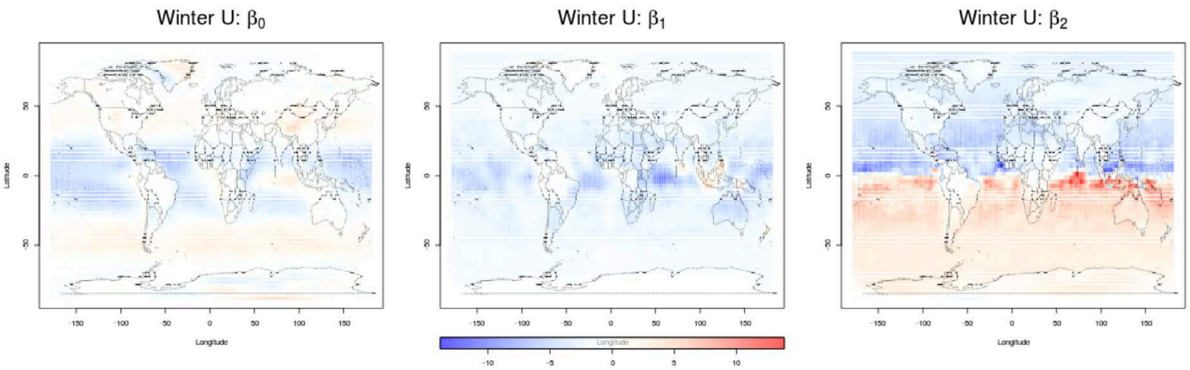

Fig. 2: Posterior means of model coefficients for U component of wind for winter data.

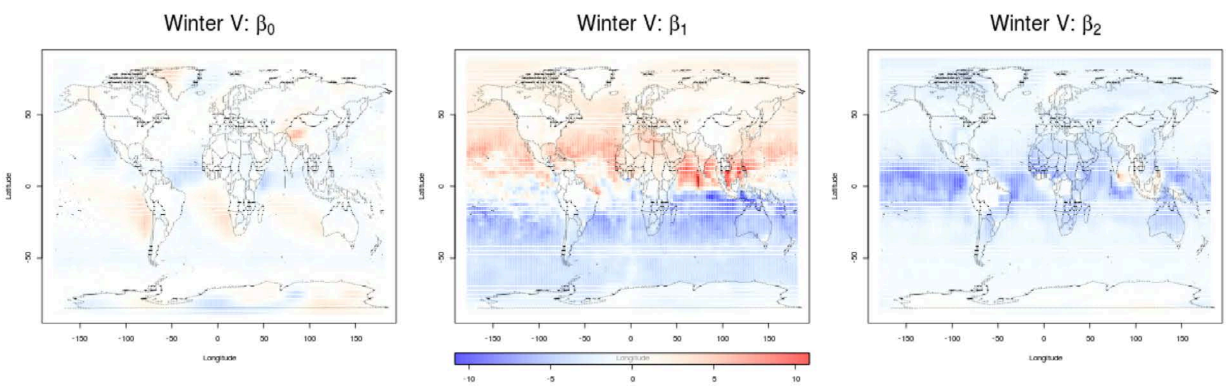

Fig. 3: Posterior means of model coefficients for V component of wind for winter data.

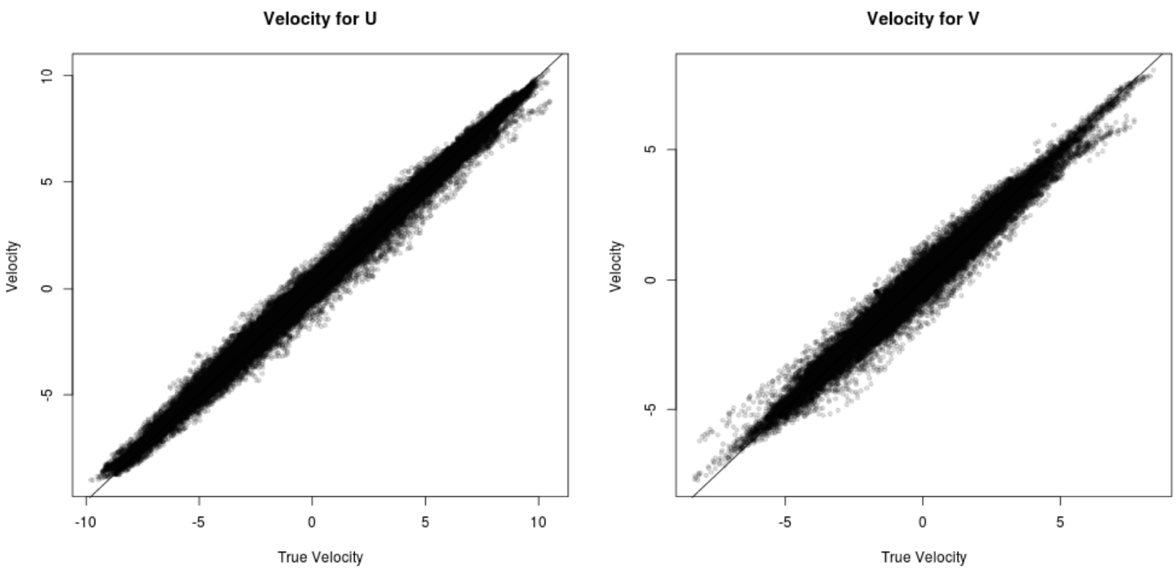

Fig. 4: Surface prediction vs. true wind velocity (m/s) for 10 years of data.

3. Separating spatial scales with model-based EOFs

We created a new hierarchical Bayesian model to explicitly separate error fields that occur at different time scales. The model is an extension of traditional EOFs to incorporate spatial and temporal dependence. As described in our last report, the main building block for our models is the observation of Tipping and Bishop (1999) that EOF construction is equivalent to maximizing a particular probability model with respect to the data. EOF computations decompose errors into p spatial fields, which we denote as $m_1,...,m_p$, each scaled by p time series, which we denote as $z_1,...,z_p$. The standard probability model corresponding to EOFs assumes that each spatial field m_i is independent across locations and that each time series z_i is independent through time. Our Bayesian method works by assigning a prior distribution to each m_i that encourages nearby locations to behave similarly, and a prior distribution on each z_i to encourage temporal structures that exhibit characteristic frequencies. These prior distributions are modeled as Gaussian processes with prescribed covariance structures.

Previously we applied this model to simulated data. We have now applied it to sea surface temperature data and compared the results to a traditional EOF analysis. As shown in Figs. 5 and 6, the results are similar, but the hierarchical clearly separates two very different scales of temporal variability. Another main advantage of the hierarchical model is that locations that have some missing data can still be included, whereas these must be thrown out in traditional EOF analysis. This can be seen for some Antarctic locations in Fig. 5.

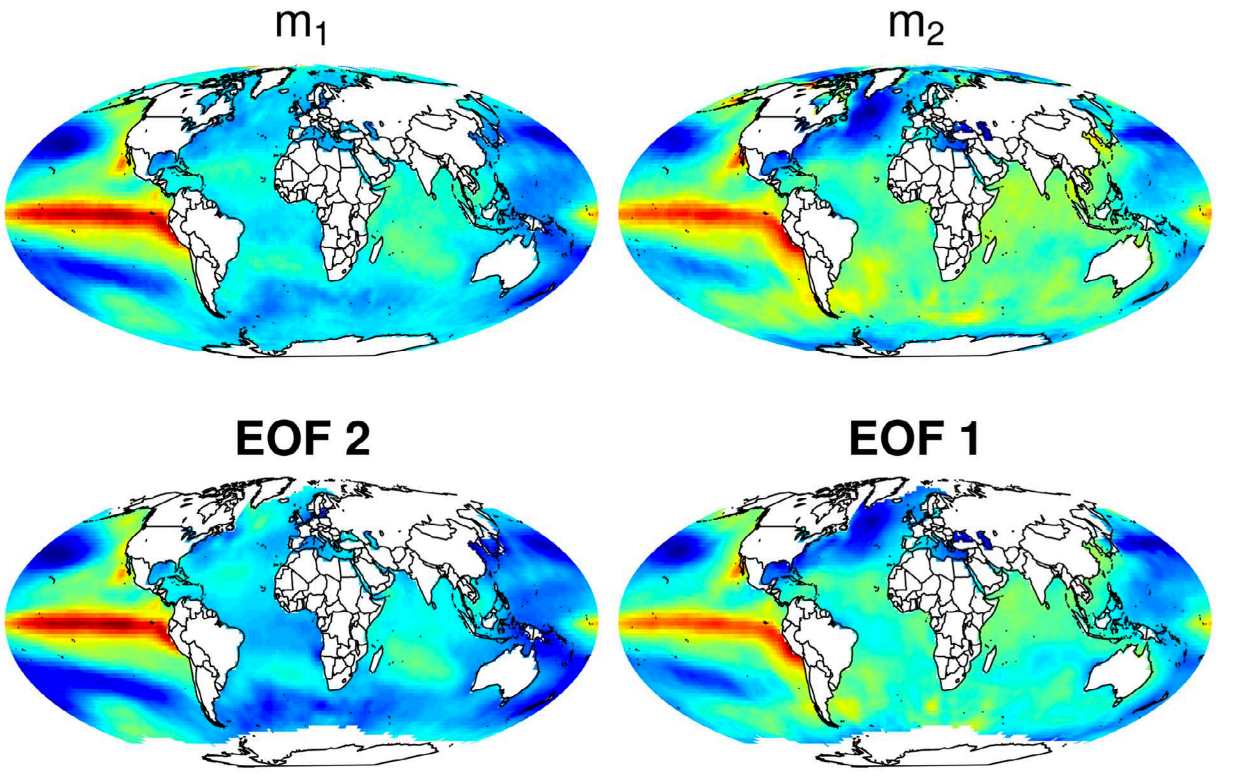

Fig. 5: Posterior mean fields and EOFs. Note that the ordering of the posterior mean fields, unlike EOFs, is arbitrary.

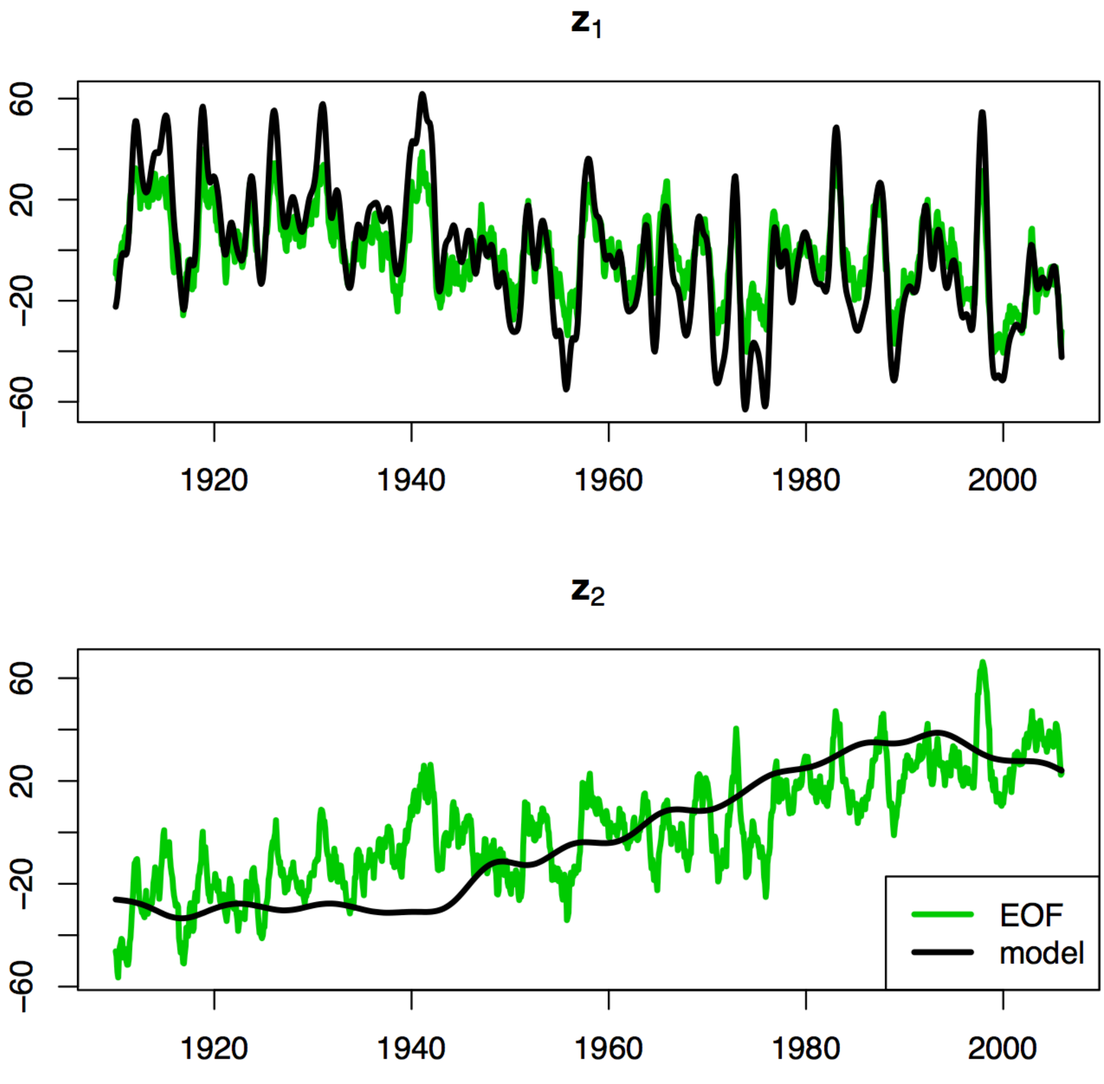

Fig. 6: Time series from hierarchical model (posterior means) and EOF analysis.

IMPACT/APPLICATIONS

The bulk of DoN day-to-day operations rely on accurate predictions of winds, seas, ceiling, and visibility. The focus of the proposed work is to identify inadequacies associated with the modeled atmospheric boundary layer. Any discoveries that enable the improvement of boundary layer modeling will ultimately have a positive impact on Navy warfighters.

The proposed methods have the potential to enable essential improvement in modeling capability. Instead of tuning models based on intuition, we are forming a foundation for objective identification of model errors. Those errors could immediately be accounted for in probablistic forecast systems, and also be subject to physical interpretation by subject experts.

RELATED PROJECTS

The MATERHORN project (http://www.nd.edu/~dynamics/materhorn/index.html), funded by ONR, seeks to improve atmospheric predictability over complex terrain. It is similarly focused on predictions in the atmospheric boundary layer. Rather than a focus on model inadequacy, MATERHORN focuses on field programs aimed at improving models via direct comparison to observations, and quantifying optimal observing strategies for improving predictions. PI Hacker is using some of the technical developments here to aid that effort, and vice versa.

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