Linear and Nonlinear Response to Parameter Variations in a Mesoscale Model

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1. Introduction

It is widely recognized that ensemble prediction system (EPS) skill can improve when considering model error in the system design. Typical approaches include varying physical parameterization schemes or entire modeling systems within an EPS, and including stochastic terms in the dynamical equations. But perhaps the simplest approach to accounting for uncertainty in a model is to perturb inherently uncertain parameters within sub-grid parameterization schemes. Although it almost certainly cannot introduce all the modes of variability produced by other methods, its simplicity alone suggests that its effect on prediction skill and variability deserves quantitative scrutiny. In this work we seek to understand how perturbations to uncertain parameters manifest in a mesoscale model, and evaluate the potential for use in EPSs or data assimilation systems that can exploit ensemble covariances and linear or nonlinear responses.

2. Experiment Description

A set of four parameters (table 1) are varied, corresponding to one each in cumulus, cloud microphysics, boundary-layer turbulence, and radiation schemes within the Weather Research and Forecast (WRF) mesoscale numerical weather prediction model (Skamarock et al. 2008). Parameters are drawn only once from distributions intended to capture the uncertainty estimated by experts and reported in the literature. Each set of parameters is drawn with a Latin Hypercube Sampling technique that ensures the parameter sets are independent and fill the four-dimensional space spanned by the parameters. The parameter sets are then fixed and an ensemble of 10 members uses them for approximately 30 ensemble forecasts during October 2006 over East Asia that are also subject to initial-condition, lateral boundary-condition and land-surface uncertainty.

Scheme	Parameter	Units	Min	Mean	Max	Meaning
Cumulus (Kain-Fritch)	R	m	-300	0	300	Sub-grid cloud radius
Microphysics (WSM5)	N_0	m^{-4}	2e6	8e6	2e9	Marshall-Palmer intercept
PBL (YSU)	A_R	none	0.1	0.15	0.3	Countergradient coefficient
SW Radiation (Dudhia)	α_{CA}	none	2e6	1e5	2e5	Clear-air scattering

Table 1: Parameters chosen for perturbation in these experiments. Latin Hypercube Sampling from β distributions, describing the uncertainty (minimum, mean, maximum) in each parameter, provides independent points that evenly fill the space defined by the parameters.

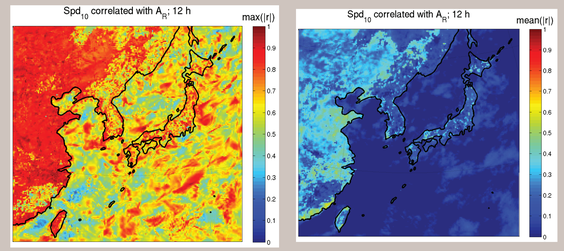

Figure 1: In (a) the maximum absolute correlation coefficient between A_R and 10-m wind speed during the experiment. In (b) the mean of the absolute correlation coefficients at each grid point. Correlations can be large and exceed a magnitude of 0.9, especially over land. Experiment-mean correlations are near 0 over the oceans with greater values between 0.3-0.4 over land. Typical correlations are weak, but correlations can locally be strong. Note that strong correlations do not necessarily translate into a large sensitivity.

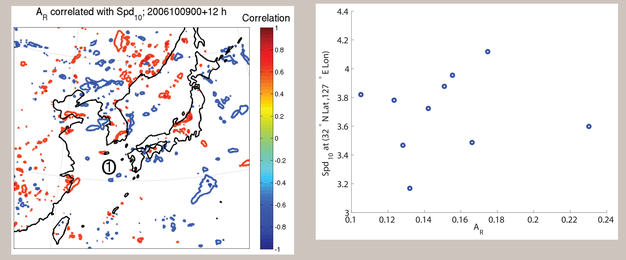

Figure 2: In (a) a map of the correlation coefficient between A_R and 10-m wind speed valid 1200 UTC 09 October 2006. Contours are every 0.1, and only those points with p-values incidating greater than 90% confidence in the correlation are contoured. In (b) the scatter between A_R and 10-m wind speed at the point denoted with a '1' in (a). Random-like relationships between the parameters and predictions are common.

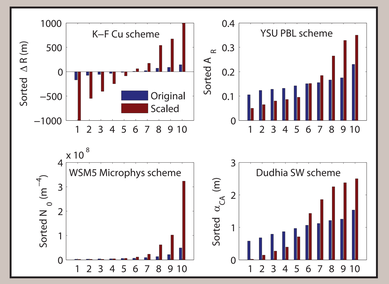

Figure 3: Parameter distribution scaling is used for testing linearity hypothesis. Original and scaled parameters are shown sorted for presentation. Distributions are scaled by a factor of approximately 7.5 about the mean, where the scaling factor was chosen based on comparing the ensemble spread of the initial multi-parameter ensemble with a multi-scheme ensemble.

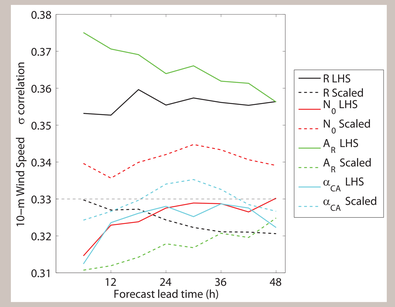

Figure 4: Standard deviations of time-space distributions of correlation coefficients between 10-m wind speed and various parameters. The thin dashed line at 0.33 is the expected value of the standard deviation, computed from a very large sample of correlations of random normal distributions of size 10 (the ensemble size). Only AR and and R appear to elicit a meaninful linear signal. Scaling the parameter distribution destroys thesignal of linearlity.

3. Methods

We explore linear and nonlinear response of surface temperature (T_2), water vapor mixing ratio (Q_2), and wind speed (Spd_{10}) predictions to parameters with the following:

a. Linear correlation coefficient between parameter distributions and ensemble forecast distributions at each grid point. Mean and maximum absolute correlation coefficient computed over the month-long experiment summarize the correlation. Results quantify whether a linear response is persistent and widespread or intermittent and local.

b. Subjective evaluation of joint parameter-prediction covariance when linearity is not apparent. This demonstrates responses that appear random or nonlinear.

c. Increase the spread (scale) the parameter distributions, re-run the experiment, and re-assess the correlations. This determines whether greater parameter variation leads to the same degree of nonlinearity.

4. Results

From the methods described in section 3 we find:

a. Fig. 1a shows the experiment-maximum absolute correlation coefficient at each grid point between AR and 12-h forecast 10-m wind speed. Fig. 1b shows the corresponding mean absolute correlation coefficients.

b. Figs. 2a and b shows an instantaneous correlation map and an example of a random-like relationship between A_R and 10-m wind speed. Scatters like these are common, and indicate that parameter variations do not necessarily change model biases, but rather can introduce nonlinear or random spread in the predictions.

c. To test whether linearlity holds for large parameter perturbations, parameters are scaled as shown in Fig. 3. All correlation coefficients for a parameter and predicted variable can be put into a distribution to characterize the probability of a linear response. Broader distributions indicate more instances of a linear response. Fig. 4 shows standard deviations (s) of distributions of correlation coefficients for 10-m wind speed, both before (solid) and after (dashed) scaling. Results again show the intermittency of the linear response, and also that linearity does not hold for large parameter perturbations.

Here comments about applicability for estimation, forecasting, etc.

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