Building ensembles by varying parameters: An exploration of parameter ranges

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Why consider multi-parameter ensembles?

- Rather than swapping physical parameterizations, fix model configuration and vary (uncertain) parameters within each physics scheme
  - Capitalizes on suite of schemes developed/tuned together
  - Only one set of schemes to maintain and improve
  - Opens possibility of estimating parameters given observations

Parameter distributions

Parameterization	**Parameter/Variable**	**Min**	**Mean**	**Max**
Cu (Eta KF)	Additive uncertainty on R	-300	0	300
PBL (YSU)	A_R (Noh et al. 2003)	0.1	0.15	0.3
Microphys (WSM 5)	N_0 for rain (M-P)	2E6	8E6	2E9
Radiation (Dudhia)	Clear-sky SW scattering α_{CA}	2E-6	1E-5	2E-5

First-order effects

- Cloud radius R affects vertical redistribution of heat, moisture, and momentum in the KF Cu scheme.
- PBL entrainment rate is directly proportional to A_R.
- N_0 determines both the mean drop size and the slope of the distribution; rain rate.
- Scattering α_{CA} is inversely proportional to direct incident solar radiation.

Latin Hypercube Sampling (LHS)

- Seek parameter vectors that are evenly dispersed within the space spanned by $[\Delta R, A_R, N_0, \alpha_{CA}]$
- LHS provides:
  - Samples on U[0,1] for each parameter
  - Each draw is independent
  - Parameters are independent from each other

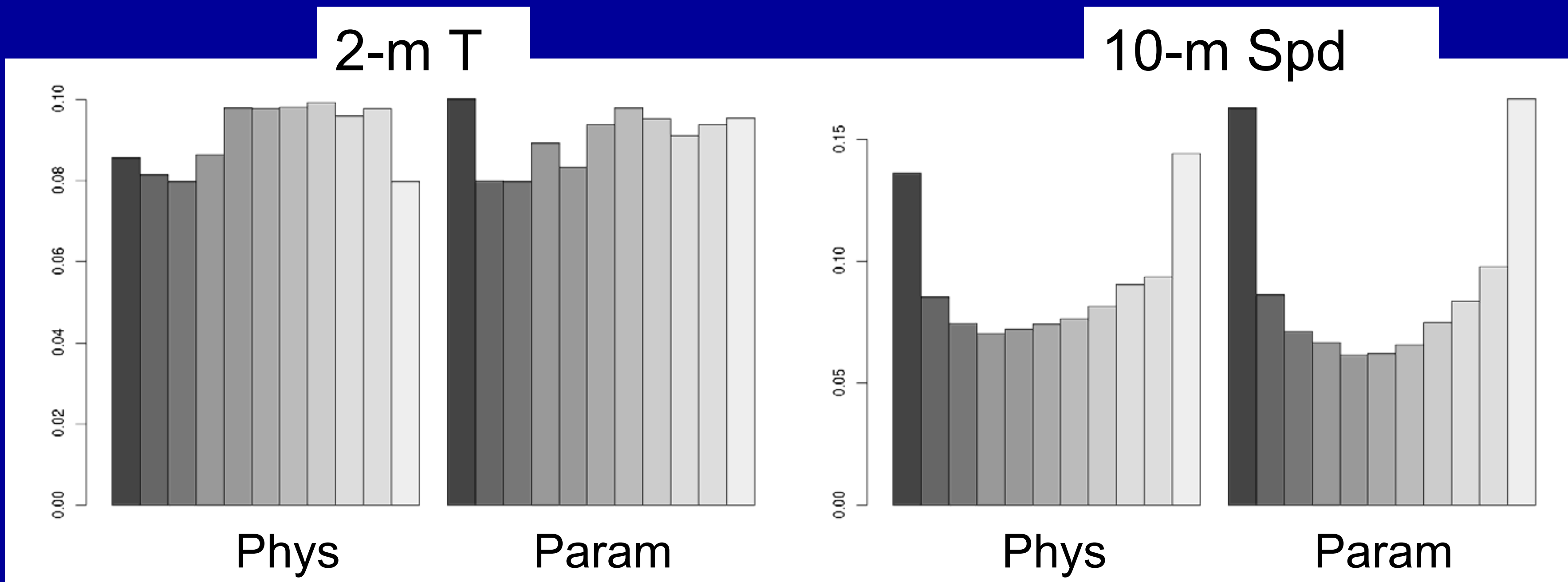
Experiment

- October 2006, Korean domain
- 00 and 12 UTC initialization on odd days (28 total forecasts)
- 60-h forecasts
- 45/15km one-way nested
- ICs and LBCs from the GFS ensemble

Results today are from domain 2 runs

Performance

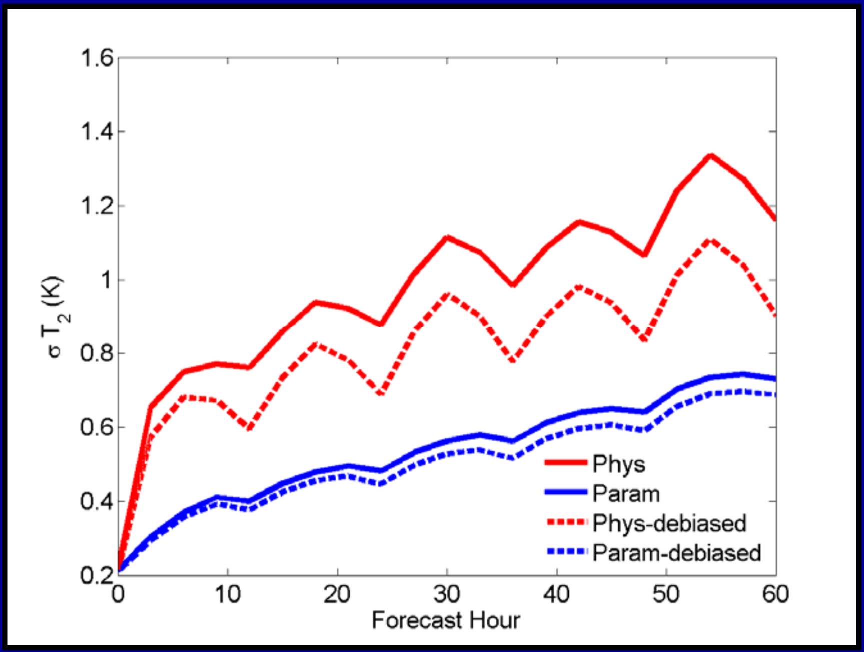
E.g. 60-h rank histograms:



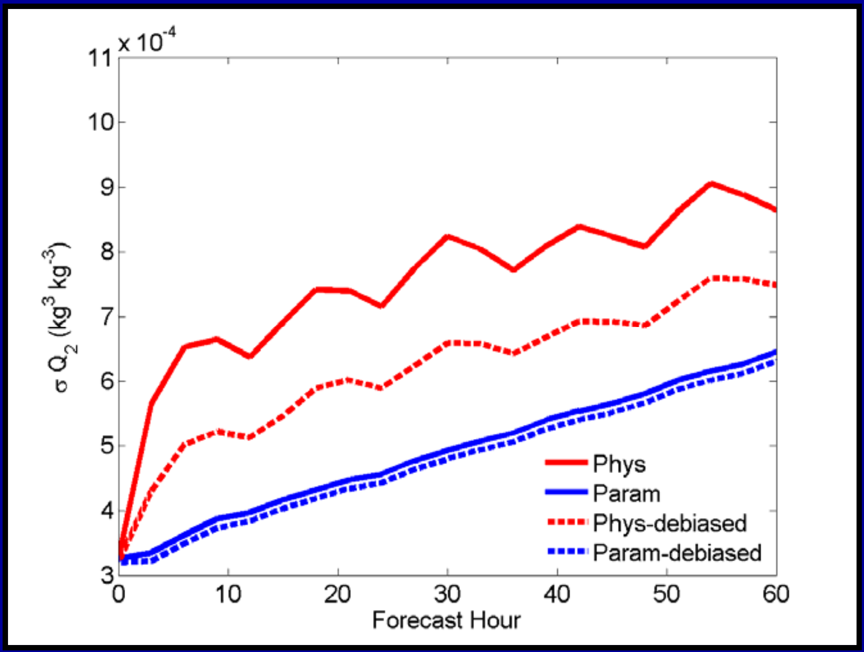
All metrics show similar results … little difference in skill

Ensemble spread

Std 2-m T



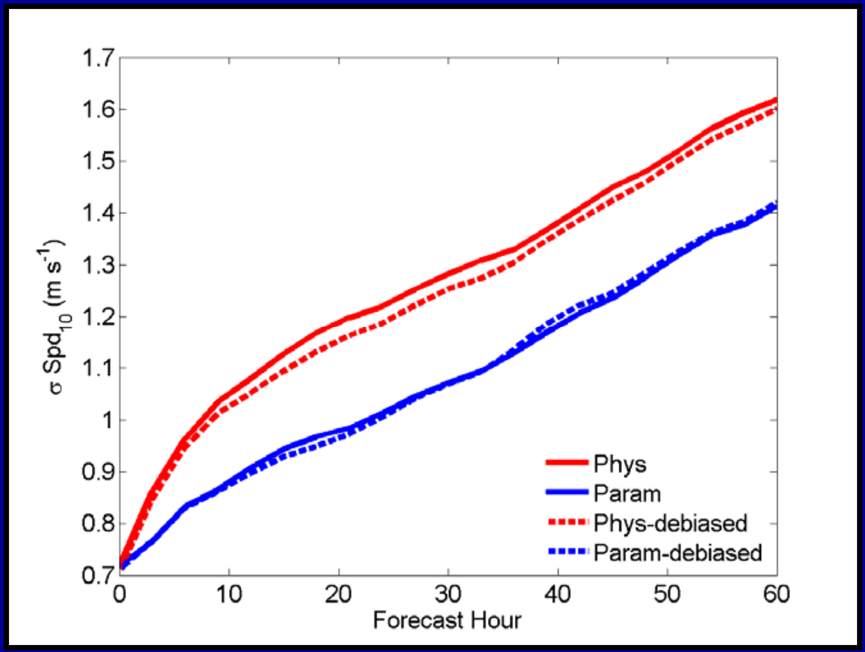
Std 2-m Q_v



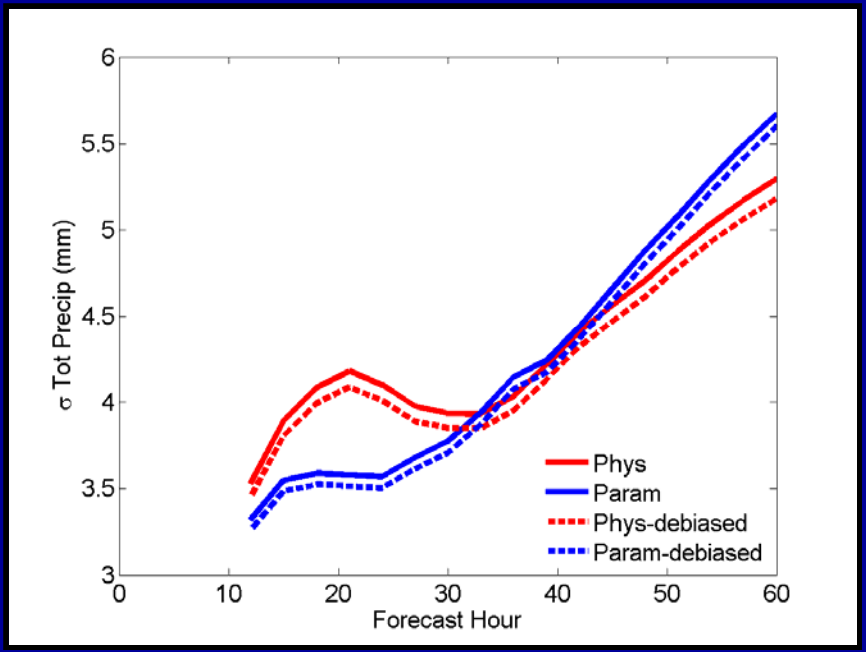
Month-long individual member mean at each grid point and forecast lead is removed before computing spread shown with dashed curves.

Ensemble spread

Std 10-m Spd



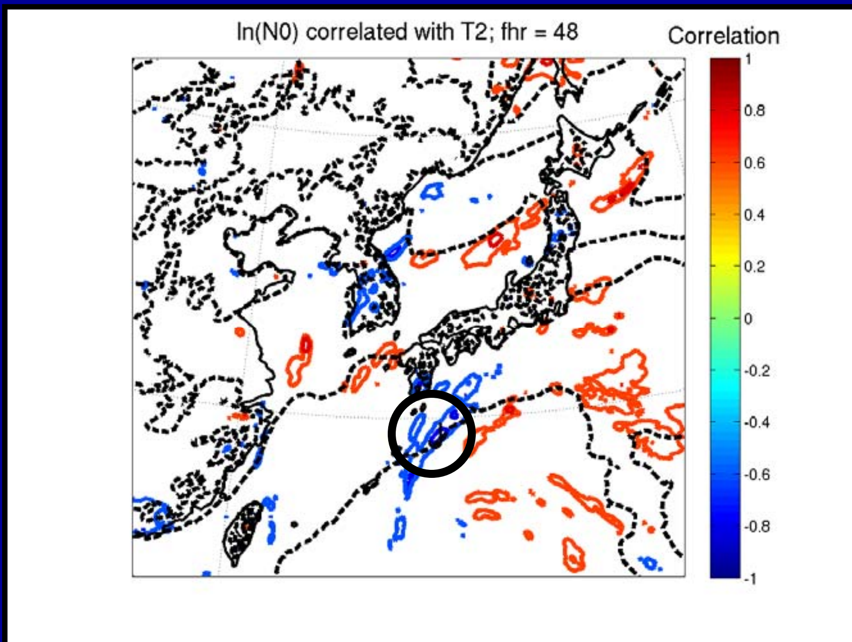
Std Total Precip

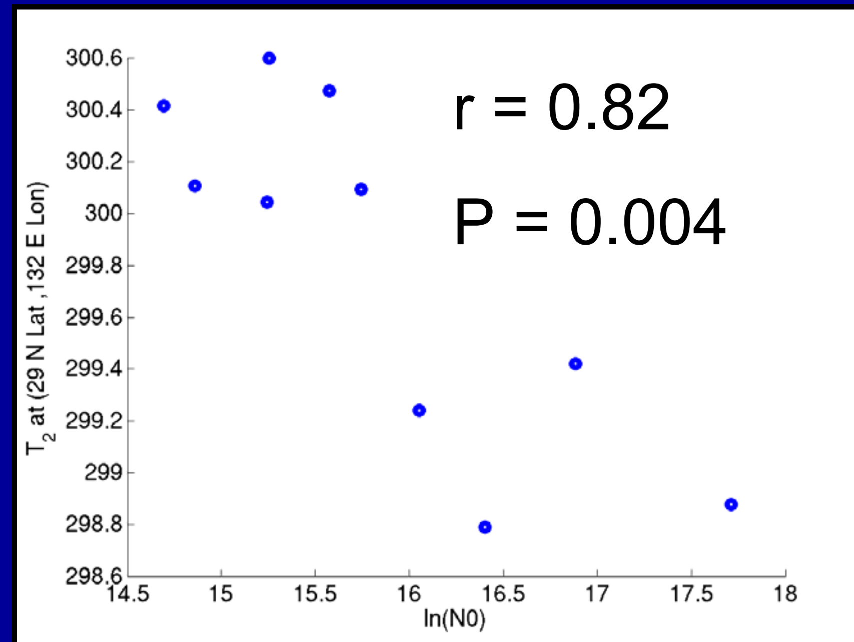


Month-long individual member mean at each grid point and forecast lead is removed before computing spread shown with dashed curves.

Exploiting linear sensitivity

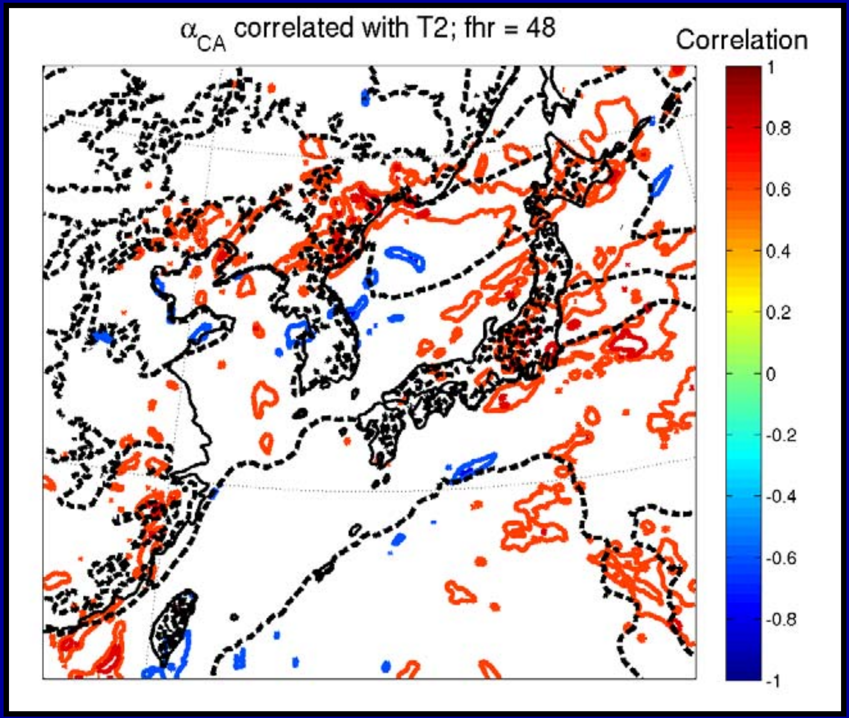
Single-case example:

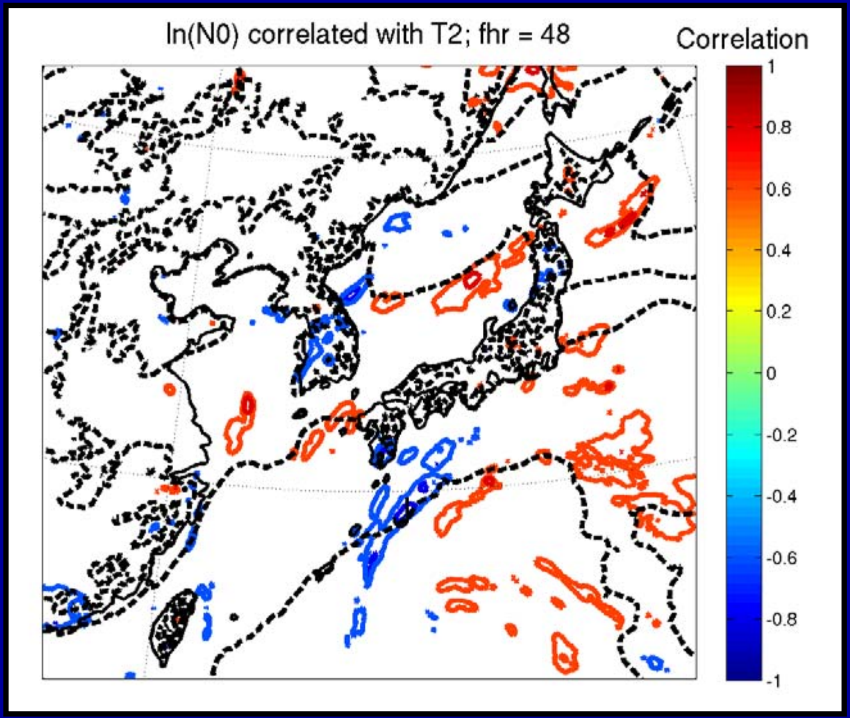




Local regions of linear response, with high confidence

Non-trivial response





Response can be in different directions

Reverse the question:

How large do parameter perturbations need to be to match the spread of the multi-physics ensemble?

Choose scaling factor α such that:

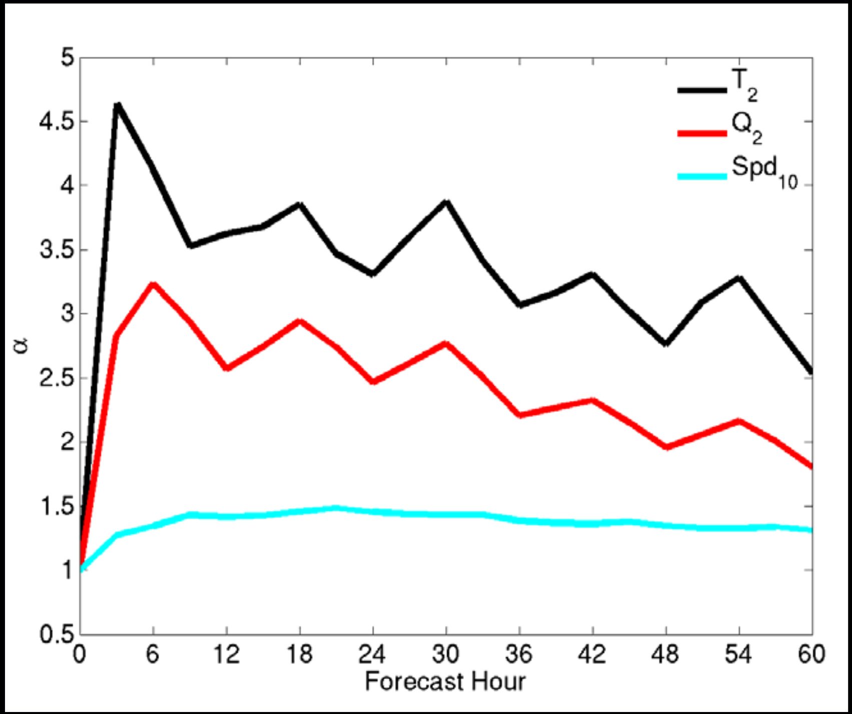
$$\text{multi-physics spread} = \alpha \times (\text{multi-parameter spread})$$

$$\left(\overline{\sigma_f}^{ij}\right)_{phys} = \left[\frac{1}{IJN}\sum_{ij}^{IJ}\sum_{n}^{N}\alpha^2\left(x_f - \overline{x_f}^e\right)^2\right]_{param}$$

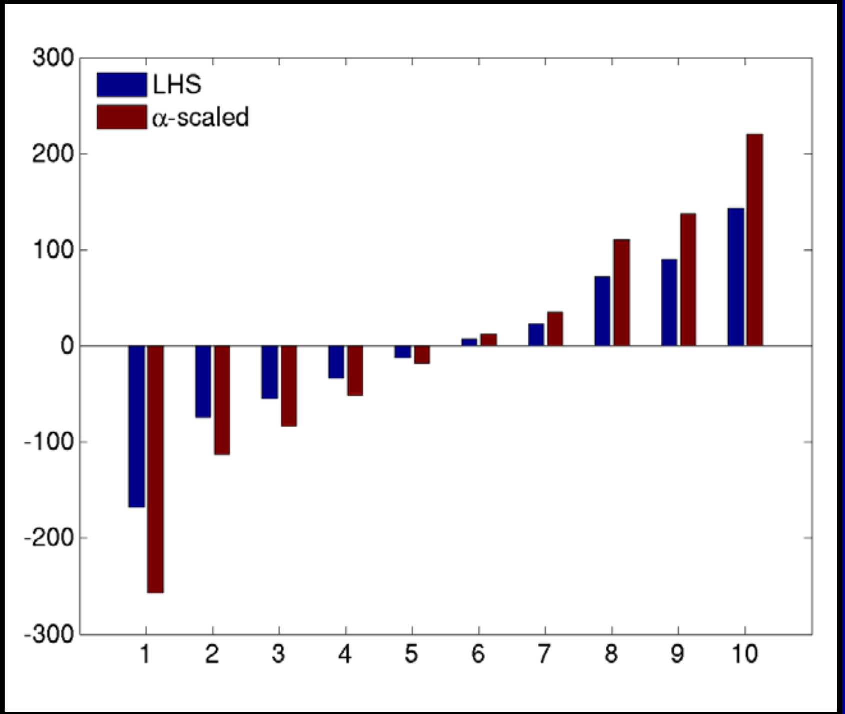
IxJ grid points and *N* ensemble members

Scaling the parameter distribution

Spread ratios



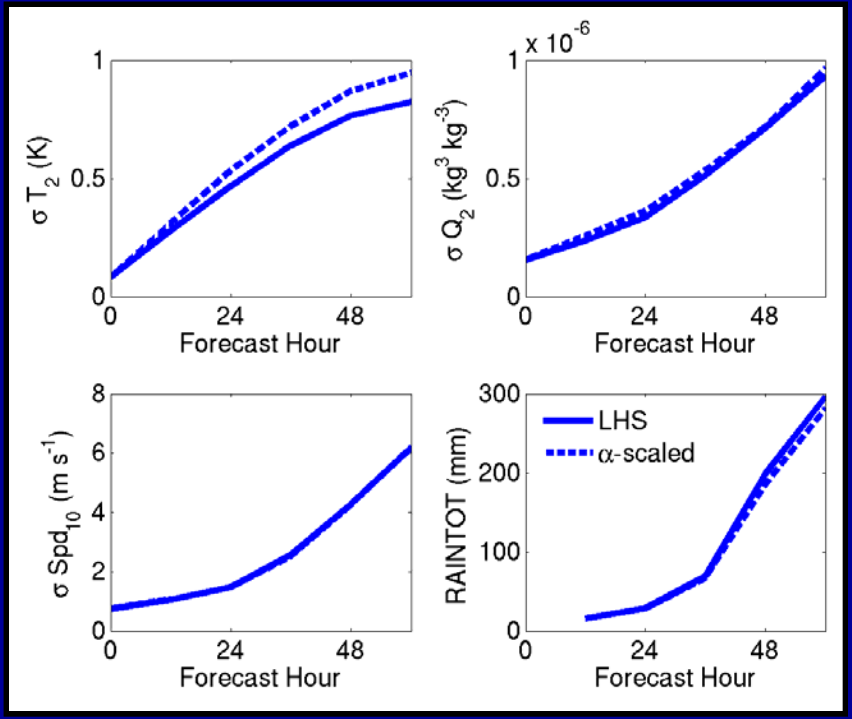
E.g. for KF cloud radius R



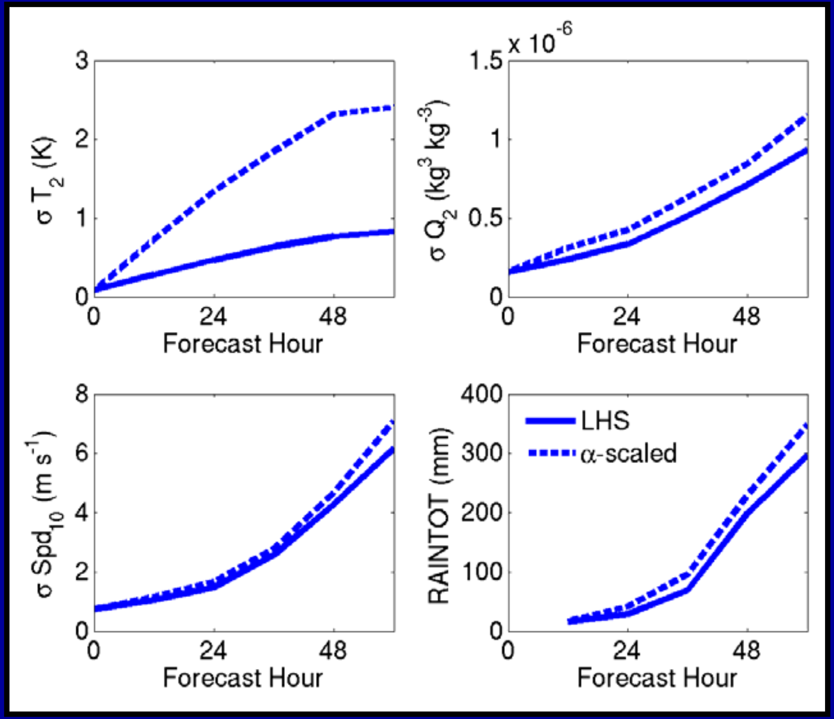
$\alpha \approx 1.5$ after averaging over times and variables*

Sensitivity to parameter spread (only two cycles)

$\alpha \approx 1.5$



$\alpha \approx 7.5$



Summary

- Probabilistic skill is similar for multi-physics and multi-parameter ensembles.
- Biases appear resistant to large parameter perturbations
- Where linear relationships between parameters and forecasts are detectable, they appear to hold under parameter perturbation scaling
- Local regions of a linear response is present for entire forecast period
- In a mean sense, forecast spread in some variables (precip, wind speed) is resistant to large parameter perturbations

Way forward

- Analyze results to suggest different parameters candidates for perturbation
- Consider an additive noise assumption to choose α
- Run month-long test for our best guess at useful scaled parameter distributions