Model-error estimation and modelling: first results

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Moscow, 6 Sept 2010

Motivation

Needed for both ensemble forecasting and ensemble data assimilation

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A fundamentally unsolved problem

Background

All practical schemes are essentially ad hoc:

- Multiplicative covariance inflation
- Additive covariance inflation
- Stochastic physics
- Stochastic kinetic-energy backscatter
- Perturbed parametrizations (parameters)
- Varied model
- Multi-model

Scope

1. Confine to a mixed multiplicative/additive model-error model
2. Adopt the Gaussianity assumption
3. Attempt to develop a *rigourous* estimation technique starting from the 'first principles'
4. Use real observations and the COSMO model

Goals and time schedule

1. 2010: Devise the model-error model, the estimation technique, and obtain first results for the multiplicative model component
2. 2011: Justify the model, extend/modify the estimation technique, introduce the additive error component, and obtain conclusive and justified estimation results. Develop and test the model-error *generator*.
3. Beyond 2011: Test the model-error generator in ensemble forecasting and Kalman filtering

Model error: definition

The forecast model:

$$\frac{dX^m}{dt} = F(X^m)$$

For the TRUTH, the forecast equations are satisfied with a *discrepancy* called the model error ϵ:

$$\frac{dX^t}{dt} = F(X^t) - \epsilon$$

Model error: definition. Discrete time

$$\epsilon := F(X^t) - \Delta X^t$$

The model-error model

$$\epsilon = \mu \cdot g(F(X^t)) + \epsilon_{add}$$

Estimation methodology

In the most general terms, we compare forecast tendencies with the observed ones (we use in-situ observations)
Specifically: for lagged obs pairs, confront the model forecast tendency with the observed one:

$$d := F(X^m) - F^o \tag{1}$$

Relate d to ϵ:

$$d = \epsilon + \delta F - \Delta\eta \tag{2}$$

$$\delta F = F(X^m) - F(X^t) = \delta X^f(\delta X^a) - \delta X^a \tag{3}$$

Estimation methodology (contd.)

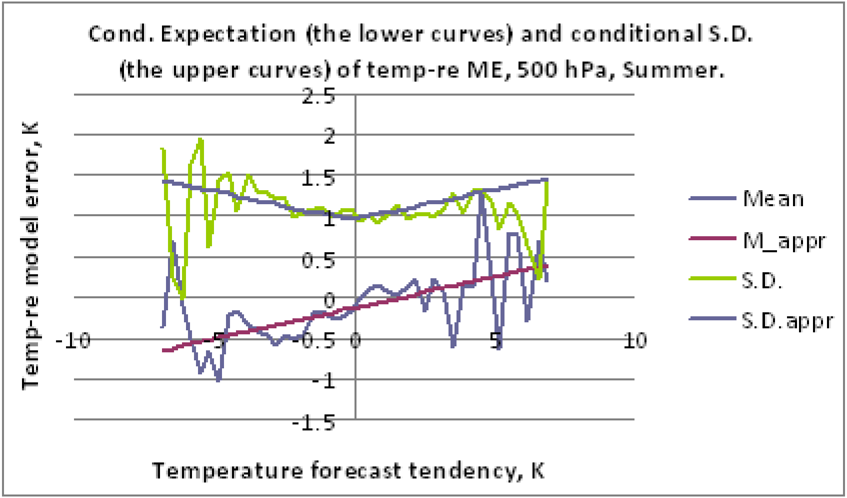
$$d = \mu \cdot g(F) + \epsilon_{add} + \delta F - \Delta\eta$$

Two statistics:

$$\mathbf{E}\left[d|F\right] = \mathbf{E}\,\mu \cdot g(F)$$

$$\mathbf{D}\left[d|F\right] = \mathbf{D}\,\mu \cdot g^2(F)$$

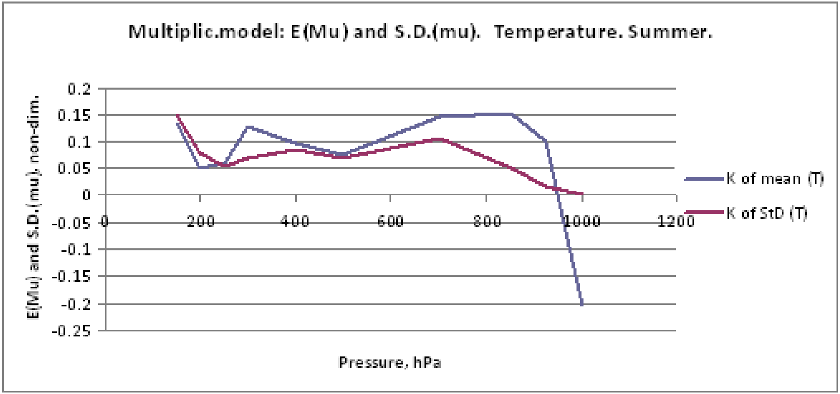
Estimation results. Multiplicative model. An example



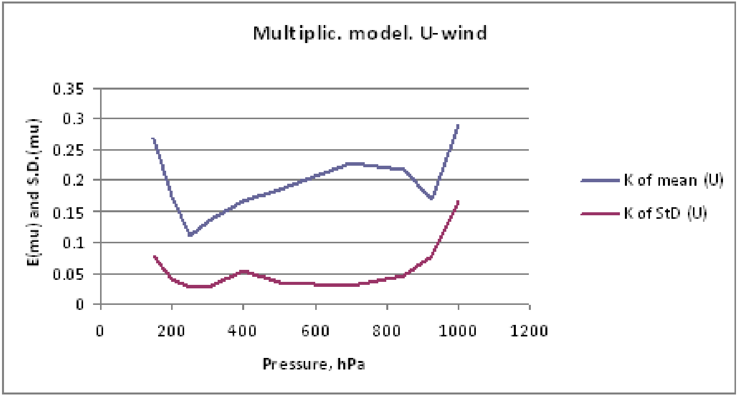
Estimation results. Multiplicative model.

The estimated multiplier statistics.

Temperature



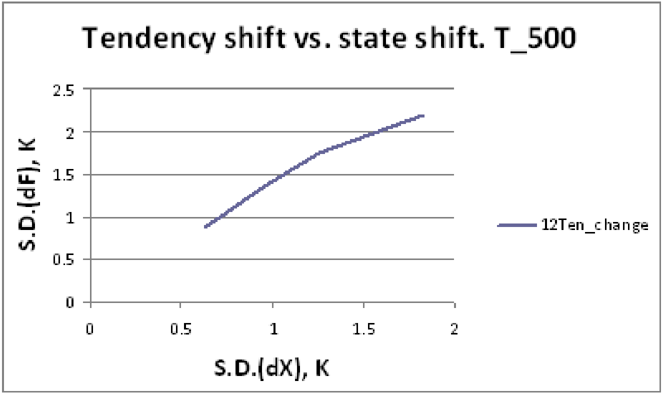
Estimation results. Multiplicative model.
The estimated multiplier statistics.
U-wind



The additive component

$$d = \mu \cdot F + \epsilon_{add} + \delta F - \Delta\eta.$$

$$\delta F = (\mathbf{M} - \mathbf{I})\delta X^a$$



Remaining issues

- Impact of δF
- Obs-err variances (including representativeness error)
- The spatial aspect
- The temporal aspect
- PBL

Conclusions

- An objective model-error estimation technique is proposed.
- First results for the multiplicative model-error component are obtained.
- Problems in model-error estimation are identified
- Options to consider:
    1. Turn to Lagrangian statistics?
    2. Focus on truly meso-scale phenomena?
    3. Look for a domain with smaller analysis error?