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The use of multiple parameterizations in ensembles.

Workshop on representing model uncertainty and error in numerical weather and climate prediction models

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June 21, 2011

Overview

- Statistical motivation,
- Closure problem,
- The ensemble Kalman filter as a diagnostic tool,
- Conclusion

Statistical motivation

The statistical motivation is the same as for multi-model ensembles:

C=0.5(A+B), with A and B: N(mean zero, variance 1) =>
C: N(mean zero, variance 0.5).

Taking the mean of independent estimate reduces error and the difference between the estimates gives information on the reliability.

Using multiple parameterizations of similar quality will improve the reliability and resolution of the ensemble system.

No perfect model

It would be neat to have the laws of nature, in the form of a forecast model, coded into a computer. One could maybe accept some unknown parameters which will eventually be estimated accurately from observations.

As we know, such a model can only exists in our dreams.

The reality is that we don't know what equations to use at any resolution we can afford to use on a computer. We might want to use different equations over ocean or land, in the tropics or the mid-latitudes or even for the night and the day.

Closure in turbulence

From a first course in turbulence (Tennekes and Lumley, 1972):

“... the closure problem in turbulence theory: one has to make (very often ad hoc) assumptions to make the number of equations equal to the number of unknowns.”

“The success of attempts to solve problems in turbulence depends strongly on the inspiration involved in making the crucial assumption”.

closure in cumulus convection

From Arakawa (1993) with regard to cumulus convection:

"most individual clouds, in which condensation takes place, are subgrid-scale for the conventional grid size of general circulation and numerical weather prediction models. Then, for a set of model equations to be closed, we must *formulate the collective effect of subgrid-scale clouds in terms of prognostic variables of grid scale*."

"The core of the parameterization problem is, therefore, in the choice of appropriate closure assumptions."

"The conceptual framework for cumulus parameterization, however, is still in the developing stage and there exist great uncertainties in choosing appropriate closures. Correspondingly, a number of parameterization schemes with different closures have been proposed."

The Grell-Dévényi ensemble convection approach

In the work by Grell and Dévényi (Geophysical Research Letters, 2002), a number of different closure hypotheses is made available in the same subroutine. *The 16 different closures can interact with any of the other closures giving a potential total of 13824 different schemes.*

It is proposed to use a Bayesian assimilation method to determine the likelihood that a particular closure is correct.

In spite of the great potential of the approach, it is more common to select available parameterizations for deep convection to form an ensemble system.

The planetary boundary layer

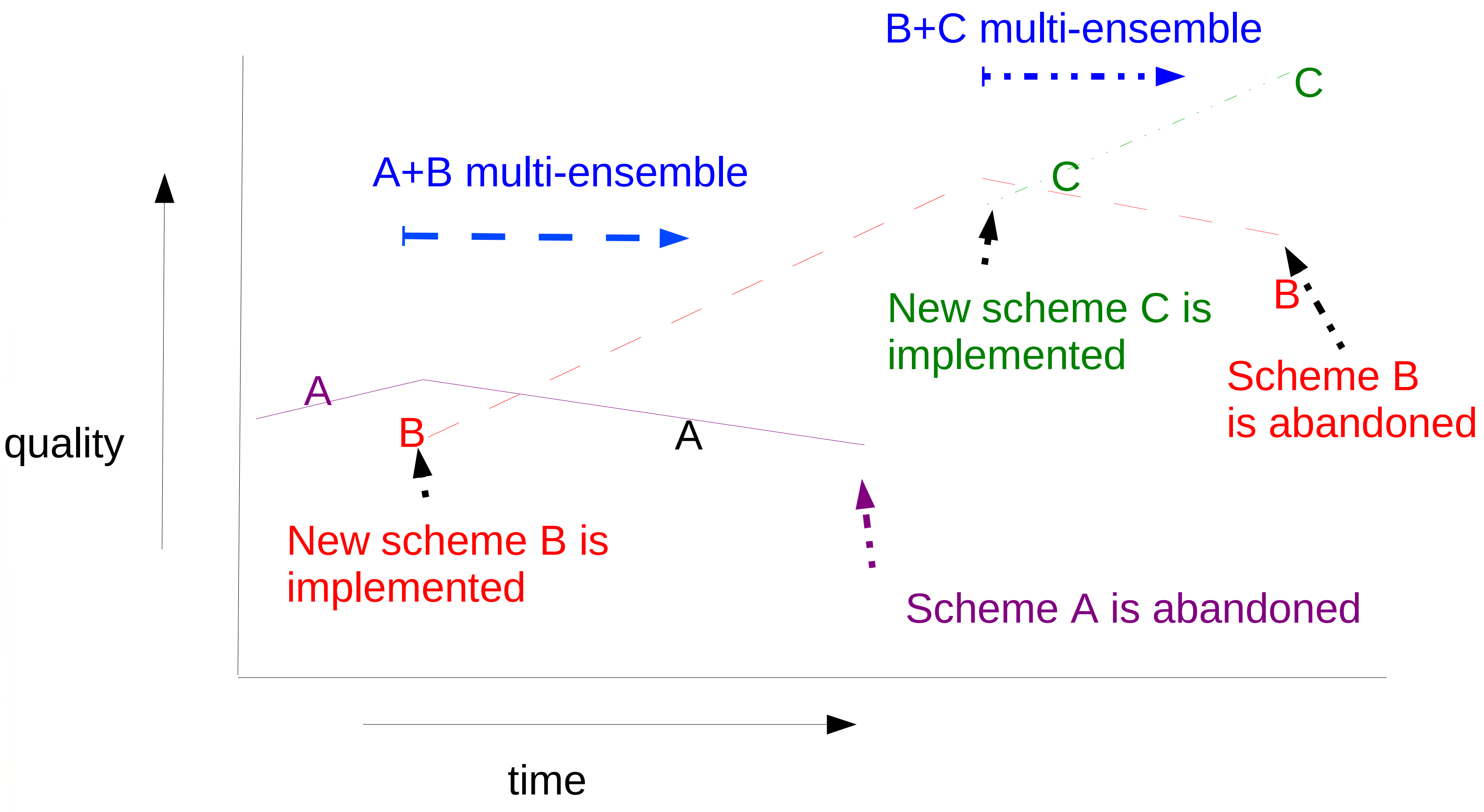
For the planetary boundary layer, we have to deal with both small-scale (local) and large-scale (non-local) turbulence.

A large number of parameterizations have been proposed. Usually these are named after people, institutions or models: Blackadar, Burk-Thompson, ACM2, Bougeault-Lacarrère, MRF, MYJ, … .

Some schemes are actually mixtures of different schemes (e.g: Blackadar + Bougeault-Lacarrère).

Ideally, in a modular environment, one would have easy access to alternative formulations while staying in the same framework.

Darwinism



B+C multi-ensemble
C
A+B multi-ensemble
C
A
B
A
quality
New scheme C is implemented
B
Scheme B is abandoned
New scheme B is implemented
Scheme A is abandoned
time

Can we learn something?

For, in particular,

1) deep convection,

2) the planetary boundary layer,

3) the surface,

we do not have a universally accepted set of equations.

Using an ensemble of multiple parameterizations accepts this unfortunate situation in a pragmatic manner.

It is a challenge to deal with the available information in a constructive manner to actually learn about model physics.

The growth of perturbations

Eventually evolving errors project on large-scale growing modes.

This observation led to the development of the breeding and singular vector methods for ensemble prediction.

Thus, whatever perturbation strategy is used, medium-range EPS systems have fairly similar spread characteristics after a few days (Buizza et al. 2005, A comparison of the ECMWF, MSC and NCEP Global Ensemble Prediction Systems).

It follows that short-range forecasts are more suitable to determine the validity of a perturbation strategy.

The Ensemble Kalman Filter (EnKF)

For an EnKF, it is crucial to have appropriate error statistics for short-range forecasts.

Fujita, Stensrud and Dowell (2007, Surface Data Assimilation Using an Ensemble Kalman Filter Approach with Initial Condition and Model Physics Uncertainties) assimilate hourly surface surface observations over a continental domain.

To sample model error they use 4 different convection schemes, 4 different PBL schemes, 3 radiation schemes and 3 surface schemes.

Conclusions of Fujita et al. (2007)

"*Particularly important are the improvements in the location and structure of mesoscale features that are seen when using the ensemble Kalman filter. The ICPH ensemble shows considerable improvement in the placement and intensity of the dryline, dryline bulges, frontal boundary, PBL depth and structure, and rainbands that form during both days studied*".

Note: ICPH=Initial Condition + PHysics Perturbation

Meng and Zhang (2007)

"*Through various observing system simulation experiments, the performance of an ensemble Kalman filter is explored in the presence of significant model error caused by physical parameterization. The EnKF is implemented in the mesoscale model MM5 to assimilate synthetic sounding and surface data derived from the truth simulations at typical temporal and spatial resolutions for the cold-season snowstorm event that occurred on 24-26 January 2000 and the warm-season MCV event that occurred on 10-13 June 2003.*

Results show that although the performance of the EnKF is degraded by different degrees when a perfect model is not used, the EnKF can work fairly well in different kind of imperfect model scenarios."

Houtekamer, Mitchell and Deng (2009)

Using a semi-operational global EnKF:

- "*The use of the multimodel option improves assimilation results in particular for temperature in the lower troposphere.*"
- "*the multimodel and PTP (Physical Tendency Perturbation) option both sample uncertainty in the physical tendencies but, by selecting alternative legitimate configurations of the model physics, the multimodel option samples that uncertainty in a more appropriate manner*".
- "*the SKEB (Stochastic Kinetic Energy Backscatter) algorithm that had been adjusted for optimal performance in the medium-range EPS could not be used to improve EnKF performance*".

Getting a complete picture

In EnKF implementations using real observations, we need "model error forcing" much bigger than can be justified or obtained with multi-parameterization, SKEB or PTP approaches. Apparently the "model error" is partly necessary to account for data-assimilation assumptions (like having independent observational errors with no bias).

To eliminate these assumptions, we would need to perform an Observation System Simulation Experiment with an EnKF and a nature run obtained with a different model. In such an environment, all unexplained error would truly be model error and adding legitimate perturbations would improve results.

The need for a list

Ideally, one would have a long list of critical decisions made in the design of the forecast model. Different centers would have different lists and by changing the list one could mimic the forecast model of another center.

Random sampling options from the list would lead to very good sampling of model error.

Problems:

i) it would be very difficult to write down a comprehensive list.

ii) parameterizations are tuned together for optimal results.

Conclusion

We have no perfect set of model equations and have some liberty to use a different set.

Different parameterizations are often selected for deep convection, for the planetary boundary layer and the surface. We need more modular forecast models in which alternative formulations are readily accessible for users. One should not aim at a having single best model.

The Ensemble Kalman Filter can be used to validate strategies to sample model error.

We don't know how large the parameterization error is. In a data-assimilation cycle, it would seem to be relatively small.

Thank you for your attention.

Questions?

Post-processing

Using multiple parameterizations, we increase the spread of the ensemble and we sample possible biases. Consequently, the need for a separate post-processing step reduces.

If post-processing is performed anyway, it needs to be done separately for each member of the ensemble (i.e. each set of parameterizations).

Ideally, for the ultimate EPS, post-processing would not be necessary. However, until the ensemble is perfect, we can get improvement from post-processing. The need for the associated long calibration periods can slow ensemble development.

Ensemble design: democratic

In a democratic ensemble design, every parameterization is used as frequently as any other.

This permits having more differences between members and thus to better sample model error.

To use the verifications for research on parameterizations, one would have to assume that the impact of different parameterizations is linear (Houtekamer and Lefaivre, 1997). In practice, for PBL and deep convection, this assumption does not hold.

Ensemble design: staircase

An ensemble can be designed such that individual members give information on individual parameterizations (e.g. Mullen and Baumhefner 1988).

Staircase model:

Member 1 = control

Member 2 = control + some change

Member 3 = Member 2 + some other change

In practice, modelers don't like to use the staircase. They much prefer comparing a single run against observations from a measurement campaign in a case-study.