

"Error Covariance Estimation in Observations, State, and Model"

Organizers / Conveners: **Tobias Necker** (University of Vienna, Austria), **Tijana Janjic-Pfander** (LMU, Germany), **Yvonne Ruckstuhl** (LMU, Germany), **Benjamin Ménétrier** (IRIT, France)

Program: (UTC)

- 15:00 15:05 Welcome
- 15:05 15:25 Ensemble Kalman filtering with colored observation noise Naila F. Raboudi, Boujemaa Ait-El-Fquih, Hernando Ombao, Ibrahim Hoteit
- 15:25 15:45 Impacts of Flow-dependent and Static Observation Error Estimation for the Frequent Assimilation of Thermodynamic Profilers on Convective-scale Forecasts Samuel K. Degelia, Xuguang Wang
- 15:45 16:05 Including observation error correlation for ensemble radar radial wind assimilation and its impact on heavy rainfall prediction

Hao-Lun Yeh, Shu-Chih Yang, Koji Terasaki, Takemasa Miyoshi

16:05 – 16:10 Time buffer

16:10 – 16:30 Background error covariance matrix estimation from multifidelity ensembles Jérémy Briant, Mayeul Destouches, Serge Gratton, Selime Gurol, Paul Mycek, Ehouarn Simon, Anthony Weaver

- 16:30 16:50 Accounting for land model uncertainty in numerical weather prediction ensemble systems: toward ensemble-based coupled land/atmosphere data assimilation Clara Draper
- 16:50 17:00 Closing: Information on summer break and upcoming sessions

Please note:

- When you login to the session before 15:00 UTC, and everything could be quiet, this is most likely because we muted the microphones.
- The times in UTC are approximate. In case of technical problems, we might have to change the order of the presentations.
 Time Zones: 15 – 17 UTC

04 – 06 pm BST (London) | 05 – 07 pm CEST (Berlin)

- 11 01 am CST (Shanghai) | 00 02 am JST (Tokyo) | 01 03 am AEDT (Sydney)
- 08 10 am PDT (San Fran.) | 09 11 am MDT (Denver) | 11 01 pm EDT (New York)

Ensemble Kalman filtering with colored observation noise

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The Kalman filter (KF) is derived under the assumption of time-independent (white) observation noise. Although this assumption can be reasonable in many ocean and atmospheric applications, the recent increase in sensors coverage and the launching of new constellations of satellites with high spatio-temporal coverage will provide high density of observations that are expected to be time-dependent (colored). In this situation, the KF update has been shown to generally provide overconfident estimates, which may degrade the filter performance. Different KF-based schemes accounting for time-correlated observation noise were proposed for small systems by modeling the colored noise as a first-order autoregressive model driven by white Gaussian noise. This work introduces new ensemble Kalman filters (EnKFs) that account for colored observational noises for efficient data assimilation into large-scale oceanic and atmospheric applications. We first consider the case where the parameters describing the observational noise time-correlations are known, and follow the standard and the one-step-ahead smoothing formulations of the Bayesian filtering problem to derive colored observational noise-aware EnKFs. We then extend these schemes to jointly estimate the time-correlations parameters along with the system state. We demonstrate the relevance of the proposed colored observational noise-aware EnKFs and analyze their performances through extensive numerical experiments conducted with the Lorenz-96 model.

Impacts of Flow-dependent and Static Observation Error Estimation for the Frequent Assimilation of Thermodynamic Profilers on Convective-scale Forecasts

Samuel K. Degelia¹, Xuguang Wang¹

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The observation error covariance partially controls the weight assigned to an observation during data assimilation (DA). Many observations, especially those collected by remote sensing instruments, feature strong flow-dependent components to their observation errors. However, operational DA systems often use static methods that assign the same observation errors across all flow regimes. To study the impact of observation error estimation for convective scale forecasts, we assimilate high-frequency thermodynamic profiles obtained from Atmospheric Emitted Radiance Interferometers (AERIs) for a nocturnal MCS observed during the PECAN field campaign. Both static and flow-dependent methods for estimating the observation error are proposed and implemented.

We find that static methods cannot estimate the wide distribution of observation errors and can lead to many observations being over- or underweighted. When assimilating AERIs using such methods, the trailing stratiform region of the MCS is degraded compared to a baseline simulation with no AERI data assimilated. Extending a static error inflation method into a flow-dependent manner improves the forecast skill by better maintaining the trailing stratiform region and suppressing spurious convection. We also evaluate a static and flow-dependent implementation of the Desroziers method that estimates the full observation error covariance using the innovation and analysis residuals. Both implementations similarly improve the trailing stratiform and spurious precipitation with the flow-dependent method producing the best forecast. The forecast improvements from these novel observation error estimation methods are primarily linked to increased errors for some moisture retrievals. These results indicate the importance of accurately estimating observation errors for convectivescale DA and suggest that flow-dependent methods can greatly improve the impacts of assimilating remote sensing datasets.

Including observation error correlation for ensemble radar radial wind assimilation and its impact on heavy rainfall prediction

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An assumption of uncorrelated observation errors is commonly adopted in conventional data assimilation. For this reason, high-resolution data is re-sampled with strategies like superobbing or data thinning. This diminishes the advantage of high temporal and spatial resolution that can provide essential detailed structures. However, assimilating the high-resolution data, such as radar radial wind, without considering the observation error correlation can lead to overfitting and thus degrade the performance of data assimilation and forecasts. This study uses the radar ensemble data assimilation system, which combines the Weather Research and Forecasting model and Local Ensemble Transform Kalman Filter (WRF-LETKF), to assimilate the radar radial velocity and reflectivity data. We present a strategy to include the error correlation of the Doppler radar radial velocity in the WRF-LETKF radar assimilation system and examine their impact on short-term precipitation prediction accuracy based on the heavy rainfall case of 2nd June 2017 in Taiwan.

For radial velocity, the horizontal error correlation scale is approximately 25 km according to the innovation statistics. The introduction of correlated observation error for radar radial wind exhibits more small-scale features in the wind analysis corrections as compared to the experiment using the independent observation assumption. Consequently, the modification on wind corrections leads to stronger convergence accompanied by higher water vapor content, which enhances local convections. This results in more accurately simulated reflectivity and short-term precipitation. In particular, such an advantage is identified for the threshold of extreme heavy rainfall at small scales according to probability quantitative precipitation forecast and fractions skill score.

Background error covariance matrix estimation from multifidelity ensembles

BRIANT Jérémy	- IRIT-CNRS, CECI-CNRS, Cerfacs, France
DESTOUCHES Mayeul	- Cerfacs, France
GRATTON Serge	- Université de Toulouse, INP-IRIT, France
GUROL Selime	 Cerfacs, CECI-CNRS, France
MYCEK Paul	 Cerfacs, CECI-CNRS, France
SIMON Ehouarn	- Université de Toulouse, INP-IRIT, France
WEAVER Anthony	 Cerfacs, CECI-CNRS, France

In ensemble-variational data assimilation (DA) algorithms, ensembles are used to estimate the background error covariance matrix B. In applications with large state vectors, the numerical cost of generating ensembles is high. Practical ensemble sizes are therefore small, which results in large sampling error in covariance estimates.

The Multilevel Monte Carlo (MLMC) method (Giles, 2008), which is a multilevel variance reduction technique, may help reduce the sampling error in the estimation of B by combining ensembles of different grid resolutions. For a given computational budget, an appropriate allocation of ensembles into different fidelity levels can lead to substantial reduction of the overall sampling error. Such allocations typically consist of many low-resolution ensembles, which are less costly, while fewer are required at finer and more expensive resolutions. The focus of our work is to investigate the practical feasibility of applying such methods to the estimation of B in ensemble-variational DA algorithms.

First, the principle of MLMC methods will be introduced for the estimation of covariance matrices. We then present preliminary attempts to use MLMC to estimate a covariance matrix from 1D random fields with predefined covariance structure. Finally the theoretical and practical difficulties we foresee for applications in more complex models will be discussed. The next step in our work will be to experiment on a Burgers model and on a quasi-geostrophic model.

References:

Giles, M. B. (2008) 'Multilevel Monte Carlo Path Simulation', Operations Research, 56(3), pp. 607–617. doi: 10.1287/opre.1070.0496.

Accounting for land model uncertainty in numerical weather prediction ensemble systems: toward ensemble-based coupled land/atmosphere data assimilation

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The ensembles in the NOAA National Centers for Environmental Prediction (NCEP)'s global data assimilation (DA) and numerical weather prediction (NWP) system are under-dispersed at and near the land surface, preventing their use in ensemble-based coupled land/atmosphere DA. This study then investigates several schemes for perturbing the soil (moisture and temperature) states in NCEP's system, drawing as appropriate from methods used in the land and atmosphere ensemble DA communities. Directly adding perturbations to the soil states, as is commonly done in land-only ensemble DA systems, generated unrealistic spatial patterns in the soil moisture ensemble spread. Extending the atmospheric Stochastically Perturbed Physics Tendencies scheme to the soil states generated reasonable spatial variation in the ensemble spread, but is inherently limited in the amount of soil moisture spread that can be induced. Perturbing key model parameters that control the land/atmosphere fluxes, in this case vegetation fraction, generated realistic spatial variations in the ensemble spread. Also, by perturbing the cross-component fluxes this method induced physically consistent perturbations in the land and atmospheric that were representative of errors in those fluxes. By contrast, methods that directly perturbed the soil states interrupted the land/atmosphere two-way feedback, exaggerating forecast errors induced by soil state errors, and obscuring forecast errors induced by atmospheric state errors. Parameter perturbation has then been selected for NCEP's NWP ensemble DA system, and is now being refined within a coupled land/atmosphere Ensemble Kalman Filter. More generally, for ensemble-based coupled DA systems, ensemble perturbation methods that perturb the crosscomponent fluxes are recommended over those that directly perturb the states in one or the other component.