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Ensemble Data Assimilation Applications to Atmospheric and Carbon Cycle Science

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1. INTRODUCTION

Data assimilation methods are commonly used to address problems involving dynamical models and observations in different scientific disciplines (e.g., atmospheric, oceanic, hydrological, and carbon cycle sciences). Sharing the knowledge and experience from different disciplines is, therefore, of fundamental importance for further improvements of data assimilation methods.

In this study we address applications of ensemble-based data assimilation methods in two different areas: atmospheric science and carbon cycle science. One of the most significant differences between these two applications is in the ways the forecast error covariance (i.e., prior error information) is used. This difference arises from different dynamical models used to propagate forecast error covariance from one data assimilation cycle to another.

For example, in atmospheric applications, dynamical forecast models are quite complex (e.g., non-hydrostatic numerical prediction models), often involving chaotic forecast error growth. This property of the atmospheric dynamical models is used in Kalman filter methods, and also in novel ensemble-based data assimilation approaches: the complex dynamical models help develop complex, dynamically dependent, and often growing forecast error structures.

In contrast to the atmospheric applications, the dynamical models used in carbon flux inversion problems are often reduced to persistence (i.e., identity operators). This is done for reducing the computational cost of the more complex carbon flux inversion problems. For example, more complex dynamical models (e.g., atmospheric + particle transport models) are commonly employed only during the preparation phase: to pre-calculate the so-called Green's functions (also referred to as base-functions, or influence functions), which are then used in data assimilation as observation operators (e.g., Peters et al. 2005). Thus, complex dynamical models for the CO_2 fluxes are excluded from the data assimilation process. As pointed out in Peters et al. (2005), this could severely limit the potential for developing realistic flow-dependent forecast error covariance structures during data assimilation.

Identity operators are also used in atmospheric data assimilation problems when dynamical forecast models are not available or not known. For example, identity operators are often used to describe time evolution of model errors (e.g., Zupanski and Zupanski 2005, and references therein).

In this paper we address the issues related to using identity operators as dynamical models in both atmospheric and carbon science applications. In particular, we address the problem of dynamically localized impact of the observations.

2. DYNAMIC LOCALIZATION

One of the major data assimilation issues related to identity operators is how to define localized, yet dynamically consistent, impact of observations, since a dynamical model for defining flow-dependent forecast error covariances is not existent (i.e., it is equal to an identity operator).

To address this problem we define a "dynamic localization" based on the ratio σ_0/σ, where σ_0 is the background (or prior) error standard deviation, and σ is the analysis (or posterior) error standard deviation. We have performed initial evaluations of this localization

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approach in applications to the problems of carbon flux inversion, employing an ensemble-based data assimilation technique. The experimental results are presented in the next subsection.

3. EXPERIMENTAL DESIGN AND RESULTS

The experimental results presented here are obtained employing an ensemble-based data assimilation approach entitled Maximum Likelihood Ensemble Filter (MLEF, Zupanski 2005; Zupanski and Zupanski 2006). Regional Atmospheric Modeling System coupled with Simple Biosphere model (SiB-RAMS) is used to define atmospheric variables and surface and inflow CO_2 fluxes. Lagrangian Particle Dispersion Model (LPDM) is used to pre-calculate influence functions for the CO_2 fluxes. These influence functions are then employed as observation operators in the MLEF. Simulated observations of CO_2 concentrations from the WLEF TV tall tower in Northern Wisconsin are used in the experiments. We estimate biases $\alpha_R(x,y)$ and $\alpha_A(x,y)$, defined as space dependent, but constant in time, multiplicative corrections to the CO_2 respiration and assimilation fluxes, respectively.

In Fig. 1, the ratio σ_0/σ is shown for the bias α_R for a mesoscale domain (600km x 600km) centered over the toll tower. Results for three consecutive 5-day data assimilation cycles are shown in Fig. 1a-c. In each data assimilation cycle, 600 observations (120 per day) are assimilated. Ensemble size of 40 ensemble members is used in all experiments. As the figure indicates, the background error reduction is greatest (i.e., the ratio σ_0/σ has the largest value) where simulated observations are available (in the vicinity of the tall tower), and it decreases away from the observations. The isolines in Fig. 1 also indicate changing patterns from one data assimilation cycle to another. These changing patterns reflect the actual dynamics of the SiB-RAMS CO_2 fluxes, which are used here only as pre-calculated values. The ratio σ_0/σ for the other bias component (α_A), even though it has a different pattern, also indicates dynamically localized impact of the observations (figure not shown).

The estimates for the biases α_R and α_A and their corresponding posterior uncertainties σ_R and σ_A, obtained employing the MLEF with the dynamic localization explained above, are shown in Figs. 2 and 3. Figs. 2 and 3 indicate that both biases approach the true value (equal to 1.0 non-dimensional units) at the tower location, and the background value (equal to 0.5 non-dimensional units) away from the tower. Also, the posterior uncertainties are smallest at the tower location, and increase away from the tower. This an indication that the dynamic localization has a positive impact on the bias estimates as well as on their posterior uncertainty estimates.

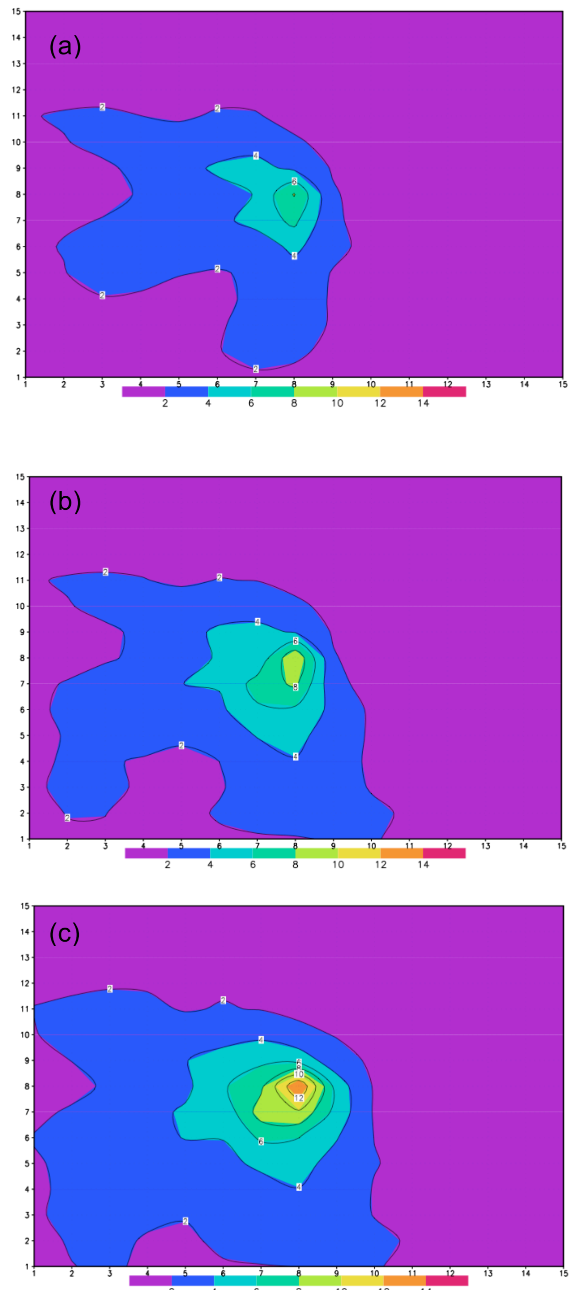


Fig. 1. The ratio σ_0/σ, calculated for the bias α_R. Results from data assimilation cycles 1-3 are shown in (a)-(c), respectively.

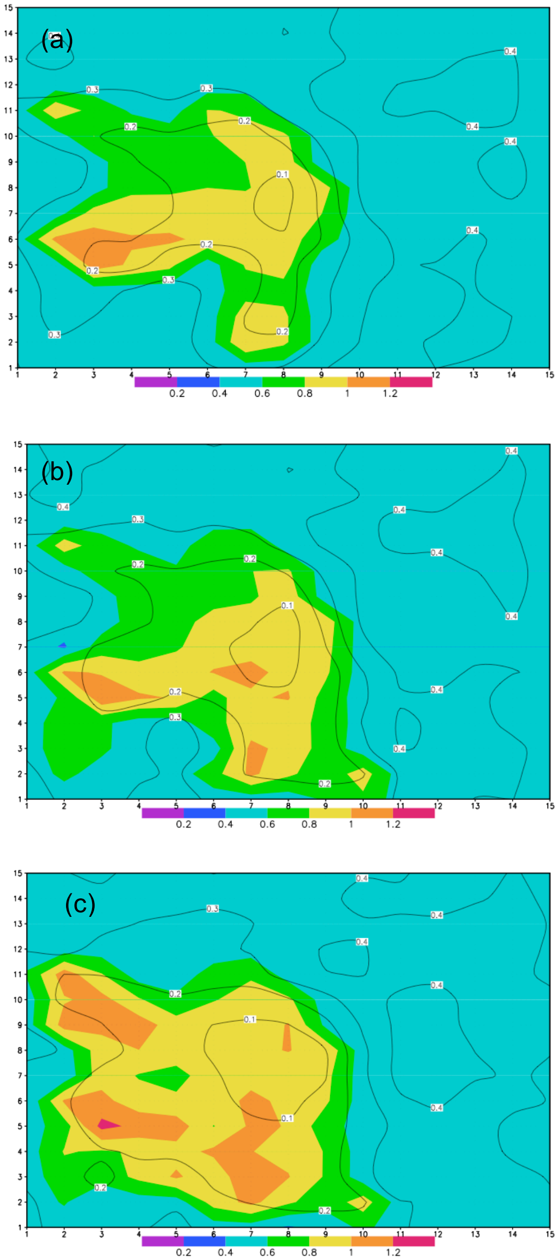
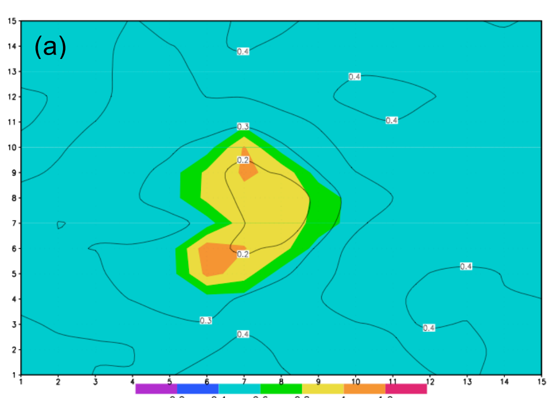


Fig.2. Estimates for the bias α_R (shaded) and its posterior uncertainty σ_R (contours) obtained employing the MLEF. Results are shown for first three data assimilation cycles in (a)-(c), respectively. The estimates and the uncertainties are passed from one data assimilation cycle to another. True α_R=1.0, prior uncertainty σ_0=0.5. Note that the uncertainty is smallest in the center of the domain (location of the tower).



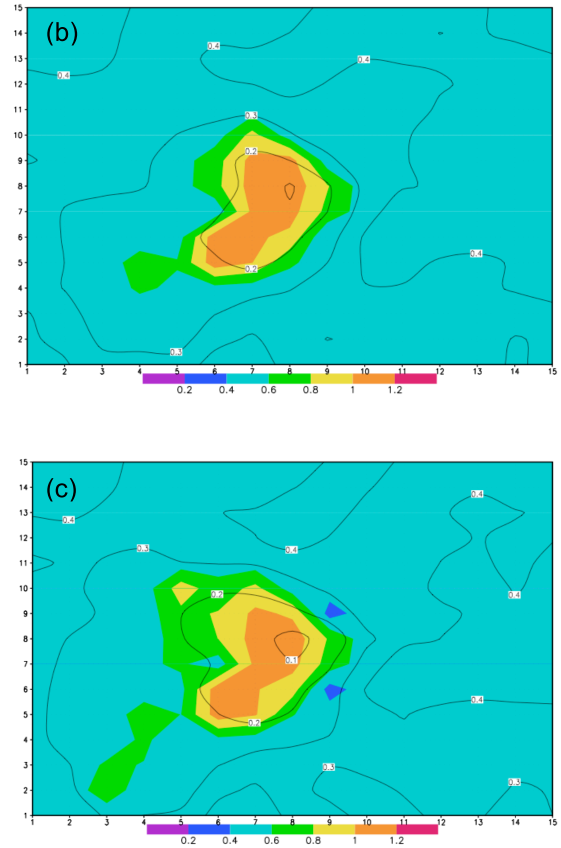


Fig.3. As in Fig.2, but for the bias α_A. Note that in both Figs. 2 and 3 the area of minimum uncertainty increases with time: *the system is learning about the truth*.

4. DISCUSSION

The results presented in the previous sub-section are encouraging, indicating that is possible to define dynamically localized impact of observations even in the cases when a dynamical model for time propagation of the forecast error covariance is not available. This is especially encouraging for the problems of model bias estimation, shared across different sciences.

These results should be taken with caution, however, since more testing of the proposed dynamic localization approach is necessary in order to be able to conclude how general this approach is. We are currently evaluating this approach in applications to carbon inversion problems employing multiple tall towers, and also in data assimilation and bias estimation problems in atmospheric science. These experimental results will be reported in near future.

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