PhD Dissertation Prospectus
Applied Mathematics and Scientific Computation
Exploring satellite data assimilation with a local ensemble Kalman filter

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Weather models forecast the future state of the atmosphere from an estimate of the current state of the atmosphere. However, the atmosphere is a chaotic physical system. That is, small differences in the current state of the atmosphere lead to dramatic differences in weather events later on. Even if weather models were perfect, small errors in the estimate for the current state of the atmosphere will yield large errors in the resulting forecasts. In order to minimize these errors, "data assimilation" seeks an accurate estimate for the current state of the atmosphere using both current and past observations.

Data assimilation schemes start with an estimate for the current state of the atmosphere provided by a prior forecast. They seek an analysis state that combines information from current observations and the forecast state (or "background"), relative to their error covariances, which quantify the uncertainty of each type of information. Many operational techniques, such as 3D-VAR and 4D-VAR, assume that the background error covariances are constant in time, spatially homogeneous, and isotropic. Ensemble schemes use the sample covariance from an ensemble of forecasts to estimate a flow dependent the background error covariance. In this way, ensemble schemes can better account for the "errors of the day" [11] than many operational data assimilation schemes [15].

Satellites provide dense observation coverage over the entire globe. However, these observations are complicated to assimilate. For example, most satellite observations are taken between analysis times, they depend on the dynamics over a broad layer of the atmosphere, and they have many biases. This dissertation studies how to assimilate satellite observations with a particular ensemble data assimilation scheme, the local ensemble transform Kalman filter (LETKF, [10]). In particular, I compare the analyses resulting from LETKF and an operational scheme, 4D-VAR, when assimilating observations between analysis times. I also examine how to select which "nonlocal" observations to assimilate in the local framework of LETKF. Furthermore, I explore how to remove satellite observation biases during the data assimilation. Finally, as part of a team I have worked to adapt LETKF to the NASA fvGCM global weather model and to assimilate real rawinsonde and AIRS satellite observations on the NCEP GFS model.

1 A comparative study of LETKF and 4D-VAR

Operational data assimilation schemes traditionally have assimilated available observations as though they, or their differences from the background forecast, occurred at the analysis time. With a growing number of observations from instruments such as satellites, many observations are available between analysis times. Four dimensional data assimilation schemes are able to more accurately take into account the timing of asynchronous observations. 4D-VAR schemes achieve this by seeking the model trajectory which best fits all the observations available over a period of time, called the analysis window [13, 3, 22, 21]. Ensemble data assimilation schemes can be made four dimensional by seeking the linear combination of the ensemble trajectories which best fits the observations available between analysis times [9].

Using perfect model experiments with the Lorenz 96 40 variable model [16], I have compared the assimilation of simulated asynchronous observations with 4D-VAR and LETKF. Both schemes have comparable error when LETKF is performed sufficiently frequently and when 4D-VAR is performed over a sufficiently long analysis time window. Furthermore, the 4D-VAR scheme remains stable for a larger range of analysis windows than LETKF.

2 Assimilating nonlocal observations with a local ensemble Kalman filter

In order to be computationally feasible, ensemble Kalman filter schemes may only evolve a limited number of ensemble members. This limited number of ensemble members is often sufficient to capture the dynamics within local regions [20, 18, 23, 12]. Therefore, some ensemble Kalman filter schemes obtain an analysis at each grid point by assimilating only those observations which are within some local region around that grid point [18, 23, 10].

Though ensemble Kalman filter schemes rely on localization, satellite observations are inherently nonlocal. Satellite observations come in two forms: radiances and retrievals. The satellite measures radiances directly. These radiance observations are the monochromatic radiation intensity from a particular frequency emitted over a column of the atmosphere. The radiation transmitted from each height in the atmosphere to the satellite is indicated by the satellite weighting function (e.g., [14]). For many radiance observations, the weighting function has large values over a broad range of heights. These large values indicate that the radiance is sensitive to the dynamics over that entire range, so that the radiance observation has an ill-defined vertical location. On the other hand, retrievals combine sets of radiance observations to obtain local observations of the model variables. The satellite retrievals are nonlocal in that their errors can be strongly correlated across significant distances (e.g., [11]).

The nonlocality of satellite radiances and retrievals complicates selecting which satellite observations to assimilate to update the model state at a grid point. Therefore, I performed numerical experiments on the SPEEDY (Simplified Parameterizations, primitivE-Equation DYnamics, [17]) model assimilating simulated radiance and retrieval observations with LETKF. These experiments support the following observation selection scheme. The state at a grid point should assimilate only those satellite radiances for which the value of the weighting function is above a tunable cutoff value within the local region around that grid point. For retrievals, the numerical experiments suggest updating the model state at a grid point by assimilating all retrieval observations within the local region around that grid point and any other retrievals to which they are significantly correlated.

I am currently using these techniques to assimilate more realistic simulated satellite radiance observations on the SPEEDY model. These techniques will also be applied to assimilate simulated and real AIRS satellite observations on the NCEP GFS model.

3 Observation bias correction

Many types of observations are prone to systematic errors in addition to the unbiased, random errors for which the data assimilation system accounts. These errors arise from two major sources: calibration errors in the instrument and errors in the operator which maps model space to observation space. Though their source differs, both types of systematic observation errors are referred to as observation biases. Satellite observations are prone to both types of systematic errors (e.g., [7]). Often, the satellites are calibrated assuming that the instrument is looking straight down. This calibration can introduce "scan bias" in observations taken from an angle. Furthermore, the radiative transfer model used to map model space to observation space is often prone to errors, called "air-mass" biases. In this study, I aim to correct such "air-mass" biases during the data assimilation.

Baek et al. [1] showed that LETKF can be used to estimate model biases online. Like Dee and daSilva [5], this online estimation is achieved by appending the bias parameters to the model state vector and updating them during the data assimilation. The Type II bias correction in Baek et al. [1] can be applied to estimate observation biases [6, 5, 4]. A similar technique has been used to find satellite observation biases for 3D-VAR data assimilation schemes [6], but has yet to be applied to ensemble Kalman filter techniques.

Therefore, I am applying this bias correction methodology when assimilating simulated biased satellite observations on the SPEEDY model. These simulated biased observations are created using the form of the bias suggested by Watts and McNally [24]. Currently, I correct these biases by assuming they are of a simpler form, namely linear combinations of the model state vectors [7, 6, 8].

4 Assimilation of AIRS observations with the NCEP GFS

Ultimately, the goal of this dissertation is to be able to assimilate real satellite observations using LETKF on an operational numerical weather prediction model. To this end, I am contributing to a group effort to assimilate satellite observations from the Atmospheric Infrared Sounder (AIRS, [2]) with LETKF on the NCEP Global Forecast System (GFS). When assimilating non-satellite observations, Szunyogh and Kostelich (personal communication, 2006) found that the analysis and forecasts resulting from LETKF are superior to those obtained from the NCEP operational data assimilation scheme, the spectral statistical-interpolation system (SSI, [19]). We have found that adding the AIRS retrieval observations further improves the state of the LETKF analysis and the resulting forecasts. This improvement is observed even though the correlations of errors in the retrievals are neglected. Furthermore, the improvement is most significant when a standard quality control procedure for the retrieval observations is used to reject observations. I am currently working to assimilate AIRS radiances, applying the techniques described above, in order to compare with the results we get using retrievals.

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