OBSERVATIONS AND DATA ASSIMILATION: DATA ASSIMILATION METHODOLOGY AND DIAGNOSTIC TOOLS

This whitepaper provides a summary of the current status of data assimilation methodologies and associated diagnostic tools and also attempts to provide a roadmap for future research in this field.

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ABSTRACT

A wide variety of data assimilation approaches and related diagnostic tools have been developed for application to geophysical systems to improve weather and climate analysis, reanalysis and prediction. This whitepaper and the associated session of the World Weather Open Science Conference focus on issues of data assimilation methodology and diagnostic tools developed for this purpose. The primary areas of application include weather, ocean, land surface, sea ice and coupled systems including two or more geophysical components. Data assimilation methods are often based on either variational or ensemble-based approaches and increasingly combine aspects of both, as in the ensemble-variational (EnVar) approach. Diagnostic tools often focus on determining quantitative estimates of model error (mostly bias), observation error (bias and covariances), or the impact of observations within data assimilation systems. Methods and tools also need to satisfy the requirements of computational efficiency on the current and future generations of massively parallel supercomputing infrastructure.

INTRODUCTION

Modern numerical weather prediction (NWP) systems and prediction systems for related geophysical components (i.e. ocean, land surface and sea ice) require accurate and timely estimates of the current state for initializing a numerical forecast model. These estimates are produced by combining information from a short-term forecast with a very large number of measurements through the process of data assimilation. The current generation of data assimilation methods for NWP typically assimilate many millions of observations to produce the initial conditions for forecast models with $O(10^8)$ to $O(10^9)$ state variables, often in less than an hour. All methods must incorporate significant approximations to make such calculations possible on currently available supercomputers. These include: assuming error distributions are Gaussian; assuming corrections to the background state are sufficiently small that simplified linearized models can accurately evolve them through time; assuming forecast error covariances for models with $O(10^8)$ or more state variables can be approximated with an ensemble of $O(10^2)$ error realizations. Some of the biggest differences between data assimilation approaches are due to a different choice of such approximations.

Current NWP systems are sufficiently complex that it is often difficult to interpret the impact of, for example, adding a new type of assimilated observation, or modifying the specified background or observation error covariances. Consequently, a significant amount of research has focused on developing diagnostic tools with the aim of better informing the choices made when working to improve analysis and forecast accuracy. These tools either employ the full data assimilation and forecasting system itself or simply use output produced by the existing system to better understand the complex internal relationships. The focus is often on the relationship between the forecast (or a measure of the forecast error) and the assimilated observation or specified parameter under examination.

SUB-THEMES

The current status of data assimilation methodologies and related diagnostic tools and possible future research directions are provided with respect to five sub-themes. The first two sub-themes address the two main categories of currently mainstream approaches to data assimilation: variational and ensemble-based. The third sub-theme covers the numerous approaches developed to diagnose the sensitivity of forecasts either to the assimilated observations or to other aspects of the data assimilation system. The next sub-theme addresses approaches for estimating and modelling the error statistics that are an essential part of any data assimilation approach. The final sub-theme deals with data assimilation methods that do not require the usual assumption of Gaussian distributed errors that is necessary to a greater or lesser extent for most approaches currently used in realistic applications.

1. Variational Data Assimilation

Background:

Variational methods use operations on model fields to define full-order descriptions of possible background errors. These, and simpler descriptions of observation errors, are at the heart of an iterative method to find the best analysis, using all available observations. The background error model can incorporate inter-variable relationships and balances, and, by using a linearized forecast model and its adjoint, 4DVar methods also represent relationships between tendencies and gradients in different variables. They are thus ideal for making best use of observations from satellites or radars which give good four-dimensional coverage of some variables, but no direct information about others. They are also very flexible, coping with a wide range of observation types and densities. Their main scientific weakness is the difficulty of making the background error model reflect flow-dependent “errors of the day”. Their main technical weakness is the building of efficient software for the iterative variational algorithm, incorporating a complex linear forecast model, for next generation massively parallel computers. While both these weaknesses might be addressed by switching to ensemble Kalman filter methods (Kalnay et al., 2007), EnVar methods instead attempt to keep the above-mentioned benefits of variational methods, while using an ensemble-based background error model.

Underpinning Research:

The most practical methods of describing "errors of the day" use ensembles, so much current research is about the use of ensemble information in variational methods (EnVar). Two approaches are possible: deriving parameters, such as variance, in a background error model from a current ensemble (Berre and Desroziers 2010); and directly using localized ensemble perturbations in a hybrid error model (Lorenc 2003, Buehner 2005, Clayton et al. 2013).

The forecast ensemble can be imported from a separate ensemble data assimilation method. The methods can be coupled more closely (Zhang and Zhang 2012), or ensembles of variational DA may be used (Bonavita et al. 2012), or the Hessian of the variational minimization can be used (Zupanski 2005).

There is some scope for improving the parallelization of the linear model in 4DVar (Fisher 2011), but most research addressing the computational weakness of 4DVar is directed towards replacing the linear model by a precalculated ensemble of trajectories, in what is known as 4DEnVar (Liu et al. 2008, 2009, Buehner et al. 2010a,b, Lorenc et al. 2014, Wang and Lei 2014).

Linkages:

The use of ensemble information in background error models is discussed below in "*Estimation and Modelling of Error Statistics*".

Many techniques, and possibly full EDA schemes, will be imported from "*Ensemble Data Assimilation*" discussed below.

Requirements for data assimilation methods are driven by those of applications such as global and convective-scale NWP and their observations; these are discussed in other papers. These requirements and the capabilities of future computers will determine which data assimilation method is most cost effective for each application.

Requirements:

We need to improve the ensembles and localization methods used in 4DEnVar so that its performance matches the more expensive hybrid-4DVar (Lorenc at al. 2014). This will need advances in localization (e.g. scale-dependent, flow-following) discussed below in "*Estimation and Modelling of Error Statistics*".

Background error models used in variational methods have many parameters which affect the performance of the method; it is practically impossible to tune them all empirically using trials. Diagnostic methods for determining them are essential.

Effective methods are needed for convective-scale EnVar for a regional ensemble nested in a larger-scale ensemble, using the latter both for boundary conditions and for modelling large-scale errors.

We need the computing power, and efficient algorithms, to apply EnVar methods to large ensembles of high-resolution models.

2. Ensemble Data Assimilation

Background:

Ensemble data assimilation is generally a Monte Carlo approach in which the ensemble forecasts represent the prior PDF. Observations are assimilated to obtain the posterior Monte Carlo samples, or ensemble members, representing the posterior PDF. Currently operational ensemble data assimilation methods assume the Gaussian PDF and are categorized as the ensemble Kalman filter (EnKF). Non-Gaussian filters are described in an upcoming section, so this section focuses on the EnKF. There are mainly two types of EnKF: the perturbed observation (PO) methods and square root filters (SRFs). Both have been shown to be successful in the operational NWP applications. The Gaussian assumption makes the problem much simpler, but non-Gaussianity arises from nonlinear evolution, nonlinear observation operators and non-Gaussian observation errors. Also, with a given computational resource, we need to find the optimal choice of the ensemble size and model complexity (resolution and physics choices). Usually we choose the model complexities so that we can afford running about 100 ensemble members, the typical size for operational ensemble prediction systems (EPS). The error covariance represented by 100 Monte Carlo samples has large sampling errors and requires forcing a finite radius of observational influences. The localization radius is an important tuning parameter of EnKF. In particular, localization for spatially averaged observations such as satellite radiances is a challenge. Also, the limited ensemble size can be a source of variance underestimation, which is usually relaxed by inflating the variance artificially. The inflation factor, a.k.a. the forgetting factor, is another important tuning parameter of EnKF.

Underpinning Research:

The fundamental idea of the EnKF was first proposed by Evensen (1994), and the EnKF was applied to global NWP by Houtekamer and Mitchell (1998). These methods apply an ensemble of parallel data assimilation cycles that use the flow-dependent background error covariance estimated from the ensemble forecasts. Burgers et al. (1998) provided the theoretical basis that these methods require perturbing observations randomly. Whitaker and Hamill (2002) proposed an alternative approach of the square root filter (SRF) that does not use randomly-perturbed observations, so that the method is more deterministic without stochasticity. Tippett et al. (2003) summarizes that SRF methods include the ensemble adjustment Kalman filter (EAKF, Anderson 2001), the ensemble transform Kalman filter (ETKF, Bishop et al. 2001), and the serial ensemble SRF (Whitaker and Hamill 2002); all of these assimilate observations one by one in series. An alternative approach was proposed by Ott et al. (2004), so-called local ensemble Kalman filter (LEKF), which assimilates observations simultaneously in each local area. LEKF was updated to the local ensemble transform Kalman filter (LETKF, Hunt et al. 2007) by taking advantage of the ensemble perturbation update of ETKF.

While different approaches to EnKF were explored, some of the EnKF approaches were implemented in operational global NWP. Houtekamer and Mitchell (2004) pioneered the first operational implementation at the Canadian Meteorological Centre for the ensemble prediction system. 4D-Var was used for the deterministic NWP system at the same time. This unique condition eventually led to the pioneering position of Canada for their hybrid 4D-Var/EnKF implementation with operational NWP system (e.g., Buehner 2005; Buehner et al. 2010a, b). Following the Canadian operational implementation, Bowler et al. (2008) of UK Met Office implemented the ETKF in operations, known as the MOGREPS (Met Office Global and Regional Ensemble Prediction System). Although the Canadian EnKF updates both ensemble mean and perturbations, the MOGREPS updates only the ensemble perturbations. In 2012, NCEP started operating a hybrid 3D-Var/EnKF data assimilation system for their deterministic global NWP (Kleist, 2013). Bonavita et al. (2008; 2010) implemented the LETKF with the Italian operational regional NWP system. Other centers including the German Weather Service, Japanese Meteorological Agency, Brazilian CPTEC, Argentinian SMN, and others have also been developing EnKF methods. Some of the centers have been using the 4D-Var, and the intercomparison has been made extensively (e.g., Miyoshi et al. 2010).

As described in the previous subsection, covariance localization and inflation are the main tuning factors in EnKF, and a number of studies have been published thus far.
- Observation-space and model-space localization: Miyoshi and Yamane (2007), Miyoshi and Sato (2007), Campbell et al. (2010), Greybush et al. (2011), Nerger et al. (2011)
- Flow-adaptive localization: Bishop and Hodyss (2007; 2009), Anderson (2007)
- Multi-scale localization: Miyoshi and Kondo (2013)
- Flow-adaptive inflation: Anderson (2007; 2009), Li et al. (2009), Miyoshi (2011)
- New directions: (large ensemble) Miyoshi et al. (2014), (ensemble-based hybrid) Penny (2014)

Linkages:

- Strong connection with hybrid. Localization and inflation techniques are mostly common.
- Hybrid does not use observation-space localization.
- Relation to non-Gaussian filters. A study incorporating the third and fourth order statistics by Hodyss (2011).

Requirements:

- tradeoff between the ensemble size and model complexities, finding the best combination to maximize the use of limited computational resources
- dealing with increasing observations. Big Data. Satellites, world’s radar data, and many more.
- localization for spatially and/or temporally averaged observations
- better localization and inflation methods

3. Forecast Sensitivity to Observations and Related Approaches

Background:

Currently there are millions of observations assimilated into operational Numerical Weather Prediction models, so that when a new observing system is introduced, the task of assimilating its observations is complex: it requires the development of a quality control (QC) system, an observation model that transforms model forecasts into observational space, and many comparisons of forecasts with and without the new observations (known as Observing System Experiments, OSEs) to demonstrate that the new assimilated observations are actually improving the forecasts. Although very sophisticated QC methods have been implemented into operations, poor quality ("flawed") observations are still accepted, and have been shown to be a main cause of sudden loss of forecast skill apparent in 5-day forecasts (e.g., Alpert et al., 2009, Kumar et al., 2009, Rodwell et al., 2013).

Langland and Baker (2004) introduced the Forecast Sensitivity to Observations (FSO) approach able to quantify for the first time how much each observation improves or degrades the forecast, using an adjoint method. This breakthrough has been adopted by others to monitor the average impact of different observing systems on the 24hr forecast error, measured by the dry energy of the error, where the truth is approximated by a verifying analysis (e.g., Gelaro et al., 2010). Cardinali (2009) developed an approach to estimate the observation impact on short-range forecasts based on 4D-Var, and Liu et al. (2009) implemented it on the LETKF. Liu and Kalnay (2008) and Li et al., (2010), created an Ensemble Forecast Sensitivity to Observations (EFSO) for the LETKF. Kalnay et al. (2012) provided an improved, simpler EFSO formulation that is more accurate and can be applied to any type of EnKF.

Another problem with the assimilation of observations, assumed to have Gaussian errors, is that the observational error covariance **R** is difficult to estimate and tune. Daescu (2008) and Daescu and Langland (2013) showed how to estimate the sensitivity of the forecast to the **R** matrix in a variational system. This major breakthrough suggests that Forecast Sensitivity to **R** (FSR) could be used to tune **R**.

Underpinning Research:

Ota et al. (2013) implemented the new EFSO into NCEP's operational Global Forecasting System (GFS) and showed that it could be used to identify the observations that led to a large regional loss of skill in a 24hr forecast, using both dry and moist total energy. They also showed that the estimation of the impact on the 24hr forecast skill from EFSO was similar to that obtained by withdrawing the flawed observations (in this case a group of high latitude MODIS winds).

Recently, Hotta (2014) showed that this approach, referred to as "Proactive QC" (PQC), could be extended so that it can be used to detect flawed observations that passed the standard QC. Major findings of his PQC work are: 1) The flawed observations can be detected as well or better in 6hr as in 24hr forecasts, and the detection is robust to the choice of analysis (e.g., 3D-Var or EnKF). 2) In 90% of the cases investigated, withdrawing the identified flawed observations with 6hr EFSO also reduced the hemispheric-scale 24hr forecast error. 3) The EFSO linear estimation of the analysis change due to denying flawed observations detected with 6hr EFSO is expected to be a good estimation of the (nonlinear) change in the analysis made without those observations. If this is true, then the PQC could be implemented into operations without introducing delays by taking advantage of the fact that operational systems usually have early analyses for short-range forecasts and "final" analyses that include delayed observations. Since the next 6hr analysis for the early run is already available, this would allow an essentially "no cost" PQC for the final analysis.

In addition to this PQC research, Hotta (2014) derived a formulation of the gradient of the forecast error with respect to **R**, similar to Daescu and Langland (2013) but based on the Kalnay et al. (2012) EFSO formulation. This Ensemble Forecast Sensitivity to **R** (EFSR) was successfully tested on the Lorenz (1996) model and on the GFS system with real observations, suggesting that the size of **R** can indeed be optimally tuned with these diagnostic tools.

Linkages:

The ability of the diagnostic tools FSO, EFSO, and FSR, EFSR to make operational Proactive QC and optimal tuning of the observation error covariances possible, opens the door to several additional improvements of the NWP systems. They include not only avoiding regional forecast skill breakdowns due to flawed observations and optimal tuning of the observation error covariance but other applications as well. One important application is to provide the developers of observation algorithms with detailed information about when and where each type of observation succeeds or fails in improving the forecasts, with all the necessary metadata for each observation needed to allow the improvement of the observation algorithm and eliminate the generation of flawed observations. Another application is the assimilation of new observing systems optimized in a much more efficient way than the current 5-day OSE experiments used to test them. Lien (2014) successfully tested this with the assimilation of precipitation, where EFSO selected the observations that improve the forecasts better than the best alternative method.

Requirements:

An essential requirement for this type of research that could rapidly be implemented operationally and improve the data assimilation system is for university researchers to have access to a system similar to the operational system in order to carry out realistic experiments. In the case described here (Hotta, 2014), this access to a supercomputer and to a lower resolution GFS system was made possible by Dr. Sid Boukabara, Acting Director of the Joint Center for Satellite Data Assimilation.

4. Estimation and Modelling of Error Statistics

Background:

The ability of all data assimilation approaches to optimally combine the information from observations and short-term forecasts depends strongly on having accurate estimates of the observation and background error statistics. For most approaches already discussed, the observation and background errors are assumed to be Gaussian and therefore only their covariances are required. Even with this simplifying assumption, the estimation of the error covariances remains a significant challenge, due to both computational and scientific aspects. The computational challenges relate to the very large number of assimilated observations (for observation error) and the very high number of state variables of typical forecast models (for background error). The scientific challenges mostly result from the fundamental issue that we only have direct access to the covariance of the difference between observations and short-term forecasts (i.e. the innovations), which is an unknown combination of the observation and background error covariances that we require. In addition, the covariance of the innovations is in observation space and therefore provides no direct information about background error in regions or for variables that are not observed. Techniques are well advance for estimating and allowing for observational bias in data assimilation, especially in the context of re-analyses. Systematic background errors are more difficult to allow for; normally the focus is on working with forecast model developers to ameliorate them.

Underpinning Research:

As already discussed in the previous sections, it has become common in many data assimilation approaches to estimate and model the background-error covariances with ensembles. Monte Carlo simulation allows an ensemble of background states to be obtained that is representative of a random sample of the background error given that all sources of uncertainty in the data assimilation and forecasting system are known and correctly simulated. Such ensemble data assimilation approaches can be made computationally feasible only by using a very small number of ensemble members, usually O(100), relative to the number of forecast model state variables. To obtain useful covariance estimates from such a small sample size requires additional information to be imposed. Among the numerous possibilities so far examined, the most efficient approach has been to assume that the spatial covariance decrease as a function of separation distance and eventually become zero at some specified distance, typically O(1000km) for global applications. Consequently, the raw ensemble covariances are modified in a way that reduces their amplitude and eventually sets to zero these distant spatial covariances. Some of the early studies demonstrating the very large benefit of spatial covariance localization include Houtekamer and Mitchell (2001) and Hamill et al. (2001). While these studies showed that even simple approaches to spatial localization are highly beneficial, other studies showed that additional improvement can be achieved through more sophisticated adaptive approaches that vary the localization function in a way that depends on the raw ensemble covariances themselves (Bishop and Hodyss, 2007 and 2009). In other approaches the optimal covariance localization is empirically computed from the output of an observing system simulation experiment (Anderson and Lei, 2013; Lei and Anderson 2014). An alternative to localizing covariances only in the spatial domain was evaluated by Buehner (2012) in which a simple localization with respect to spectral wavebands was combined with scale-dependent spatial localization. Since spectral localization is equivalent to local smoothing in the spatial domain, this is closely related studies that show the benefits of applying a spatial smoothing to variances or spatial correlations (Berre and Desroziers, 2010).

Because the true state of the atmosphere is not known, we are forced to make certain assumptions that enable the background and observation error statistics to be estimated from statistics of the innovations. A common example of this it to assume the observation error is spatially uncorrelated, whereas the background error is correlated. Following this basic assumption, one can fit a simple parameterized function to the innovation covariances that consists of the sum of uncorrelated and correlated components that are associated with the observation and background error covariances, respectively (Hollingsworth and Lonnberg, 1986). Other approaches involve assumptions that allow the background and/or observation error statistics to be computed from the output of an existing data assimilation system (Desroziers et al., 2005). In either case, the assumptions made can not be verified without having access to the true atmospheric state (Talagrand, 1999). Such approaches have been applied to estimate both spatial and inter-channel observation-error correlations (Garand et al. 2007; Bormann and Bauer, 2010). However, with all of these approaches, it is usually very difficult to independently validate the results, except in idealized experiments where the truth is known.

Another approach to estimating error covariances is quite different from those already mentioned and is closely related to the adjoint sensitivity approaches discussed in a previous section. In this approach the sensitivity of a scalar measure of forecast error is computed with respect to changes to a set of error covariance parameters (Daescu and Langland, 2013). The adjoint of the forecast model propagates this sensitivity from the forecast time (e.g. 24h after the analysis time) backwards to the time of the analysis and then the adjoint of the data assimilation system is applied. In principle, a sufficiently large ensemble of short-term forecasts with suitable spatial localization could be used instead of the adjoint of the forecast model to propagate the sensivity information backwards from the forecast time to the analysis time.

Linkages:

There are numerous inseparable links between the approaches described in this section for modelling and estimating error statistics and the research described in the first two sections on variational and ensemble data assimilation approaches. This is because the choice of data assimilation algorithm often dictates what approaches for modelling error statistics can and cannot be used in realistic applications. For example, most ensemble data assimilation approaches cannot use covariance localization applied strictly to background-error covariances, but must apply it to the covariances after they are partially or completely transformed into observation space, which may not be optimal for non-local observations, such as satellite radiances.

The approach for computing the sensitivity of forecast error to error covariance parameters is directly related to the approaches described in the previous section "*Forecast Sensitivity to Observations and Related Approaches"*.

Other more general approaches for estimating and modelling error statistics are discussed in the following section, "*Non-Gaussian Data Assimilation*".

Requirements:

With increasing computational power, future data assimilation systems will need to be capable of efficiently estimating and utilizing background error statistics from forecast ensembles with much higher number of members and with much higher spatial resolution.

Related to the previous requirement, improved and efficient approaches will be needed for covariance localization that are appropriate for the very large range of scales present in ensembles from 10km global-scale or 2km continental-scale models. This will likely require some type of multi-scale localization, on which preliminary research has already been conducted (e.g. Zhang et al., 2009; Buehner, 2012; Miyoshi and Kondo, 2013).

Finally, research is required to evaluate which assumptions or methods or observing networks are needed to be able to reliably separate innovation covariances into its observation error and background error components. Such procedures are needed for both maintaining accurate ensemble spread in ensemble data assimilation system (through adaptive inflation) and obtaining accurate observation error covariance estimates.

5. Non-Gaussian Data Assimilation

Background:

With ever increasing resolution of numerical weather, ocean, and climate prediction models and progressively complicated relations between observations and model variables, the data-assimilation problem is becoming more nonlinear. All data-assimilation methods in use today are either linear or based on linearisations. While these methods can be expected to work well for weakly nonlinear systems, new models, e.g. convection-permitting models, are highly nonlinear and standard methods are likely to fail or give strongly suboptimal results. The recent development in hybrid methods which combine variational and Ensemble Kalman Filter ideas, does not solve any of the nonlinearity problems. To some extent they even do the contrary by introducing extra linearity, e.g. by perturbing observations.

Underpinning Research:

The underpinning research in this area mainly resides in academia since NWP centres have decided to allocate resources to hybrid methods rather then to the nonlinearity problem.

This is of course understandable given the operational constraints, but does hamper rapid development in this field. Several nonlinear data-assimilation techniques do exist for small-dimensional problems, and recently serious progress has been made to higher dimensional systems. This progress has invariably been made with particle filters and with Gaussian mixture models. Both are ensemble based –a particle is the same as an ensemble member- but quite different from Ensemble Kalman Filters.

To make particle filters efficient for high-dimensional systems they have to be steered towards future observations. Ades and Van Leeuwen (2014) have used a simple relaxation technique and have shown that their Equivalent-Weights Particle Filter can be used in very high dimensional systems. Morzfeld and Chorin (2012) use variational techniques related to 4Dvar in their Implicit Particle Filter for geophysical systems. While it can be shown that the Implicit Particle Filter will be degenerate for high-dimensional systems the approach can be combined with the Equivalent-Weights idea to come up with a new nonlinear data-assimilation system. This new system would be similar to the ensemble of 4DVars used at ECMWF, however, it would now be fully nonlinear. Such a scheme would require a change of the 4DVar system as the initial condition is fixed (the position of the particle at initial time) and model evolution errors would now have to be included. An advantage is, however, that convergence of the minimisation is not crucial. Another huge advantage is that the state covariance, either climatological or derived from an ensemble, is not needed! This means that all efforts can be placed on improving model evolution error covariances, which is where the true interaction with the physics lies.

In Gaussian Mixture models the pdf is described by a set of Gaussians (see e.g. Hoteit et al, 2008). Typically, the means of the Gaussians are propagated forward with the model equations, similar to the Ensemble Kalman Filters, but the covariance of each Gaussian is not as this is too expensive. The covariances are determined ad hoc at analysis time, making this method a mix between fully nonlinear and Ensemble Kalman Filter methods. Another issue is that the filter is degenerate when the number of observations is large, which can however be alleviated by employing localisation. Note specifically that, unlike in particle filters, state covariances are needed and have to be accurate. Also hybrids between the Gaussian mixtures and particle filters have been developed, but they again have the same problem of ad hoc specification of the covariance matrices in the mixture (see e.g. Stordal et al., 2011).

Linkages:

There is a direct link to Ensemble Kalman Filters via the use of ensemble members (and the advances of parallel computing), and with the variational methods like 4Dvar to generate efficient particles as described above. There is a strong link with the work related to determining model evolution errors as these are essential to good particle filter performance. Another linkage is with 4DENVAR, which avoids the adjoint calculations.

Requirements:

One of the main reasons for the slow uptake of nonlinear data-assimilation techniques is, unfortunately, a lack of knowledge in the community misunderstanding of what nonlinear data assimilation is and how to attack it. There is a real need for systematic training in this area.

A stronger engagement of operational NWP in nonlinear data assimilation is highly desirable to be able to properly test nonlinear data-assimilation methods for operational practise. Academia neither has the resources nor the technical knowhow to do this.

A strong community effort is needed on proper model evolution error covariances. This is not only essential for particle filters, but also for existing data-assimilation methods like 4DVar and Ensemble Kalman Filters as we know that these errors are substantial and need inclusion in the data-assimilation problem.

CONCLUSION

Research on data assimilation methodology and diagnostic tools needs to continue to address the future challenges associated with the increasing complexity of forecast models and observing systems.

Acknowledgements

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Tables and Figures