

Mathematical Advancement in Geophysical Data Assimilation

Pierre Gauthier (Université du Québec à Montréal)

Kayo Ide (University of Maryland / University of California, Los Angeles)

Chris Jones (University of North Carolina at Chapel Hill / University of Warwick)

Keith Thompson (Dalhousie University)

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1 Overview of the Field

1.1 Mathematical Overview of Data Assimilation

The issue of fusing data into models arises in all scientific areas that enjoy a profusion of data. In the geophysical community, this is referred to as data assimilation (DA) and has the goal of estimating an unknown true state of the atmosphere or ocean. The most routinely performed practice of geophysical DA is numerical weather prediction. The current atmospheric state is estimated 'optimally' by fusing the relevant atmospheric observations over the preceding few hours of a DA cycle into an output computed by a large atmospheric model as a forecast based on a past initial condition. The resulting analysis of the current state is then used as a new initial condition to start a forecast of the next assimilation cycle.

The mathematical problem of fusing data into a model is both fundamental in that it aims at the estimation of an unknown, true state and challenging as it does not naturally afford a clean solution. It has the two equally important elements of observations and computational models. Observations measured by instruments provide direct information of the true state, whether they are taken in situ or by remote sensing. Such observations are heterogeneous, inhomogeneous in space, irregular in time, and subject to differing uncertainty. In contrast, computational models use knowledge of underlying physics and dynamics to provide a complete description of state evolution in time. Models are also far from perfect: due to model error, uncertainty in the initial conditions and computational limitations, model evolution cannot accurately generate the true state. In order to obtain an analyzed state that is more complete and accurate than the raw observations or model simulations by themselves, DA merges observations into the models.

The DA schemes in use have been built on a variety of mathematical theories and techniques originating in such areas as statistics, dynamical systems and numerical analysis. Recent technological advances have elevated both sides of the DA equation to a new level: innovative observing techniques have led to an enormous surge in the amount of available data, and increased knowledge of the underlying system advances geophysical modeling, while ever faster computers have given us the capability of new levels of computational modeling. Accordingly the need to develop more sophisticated yet efficient DA schemes has grown commensurately.

By its very nature, DA is a complex interdisciplinary subject. The development of effective methods of DA must now be viewed as one of the fundamental challenges in scientific prediction. Nevertheless, the part of the mathematical community interested in these issues has been limited until recently. In particular, timely and exciting subjects that badly need input from mathematicians include the potential of ensemble-based methods, the unifying effect of a Bayesian perspective, and the present shift towards probabilistic forecasts. Mathematical theories and computation such as Markov-chain Monte Carlo methods and stochastic computing give promise of significant advancement for DA. We now have a tremendous opportunity to bring

the relevant scientific areas together in a focused effort aimed at developing new approaches, understanding the underlying issues and testing the implementation of new schemes.

1.2 Background for This Workshop

This intensive workshop was organized to bring together mathematicians, particularly those working in dynamical and stochastic systems, statisticians, and domain scientists who have a vested interest in fusing data with models. The workshop aimed to host a mathematical effort for a genuinely interdisciplinary subject in that the participants will explore and define mathematical investigations necessary to advance DA further beyond the current state-of-the-art.

To lay the groundwork and respond to the growing need for mathematical and statistical techniques, a pilot mathematical program on DA was run collaboratively by the Statistical and Applied Mathematical Sciences Institute (SAMSI) and the Institute of Pure and Applied Mathematics (IPAM) during spring 2005. Communication between the various groups is being established. The area is now ripening for fostering effective collaborative efforts as a community begins to gel around the key questions and mathematicians are brought in to tackle the hard problems. The timing of this workshop is chosen judiciously to collectively maximize the impact of this workshop and keep up the momentum after three years since the pilot program.

2 Recent Developments and Open Problems

Data assimilation has made significant progresses recently. Progresses may be categorized mainly into two areas. One area concerns the development of mathematical approaches to assimilate data. In the past, two approaches have been considered as the advanced approach. They are the variational approach (either 3D-Var or 4D-Var) and the sequential approach (mainly ensemble Kalman filter for large-dimensional problems). Both approaches basically solve the same problem but make different approximations in order to be computationally feasible for large atmospheric and oceanic problems. A new approach based on the Bayesian estimation has been gaining its popularity because it makes less approximations than the variational and sequential approaches. However, the most severe limitation of the Bayesian approach so far is that it quickly becomes computationally unfeasible to implement as the dimension of the system increases. The other area concerns how to deal with the complex systems like the atmosphere and the oceans, while the currently available models cannot fully represent such systems.

As more mathematicians get involved in data assimilation, we expect that significant progress will be made in the coming years. Some open questions and challenges raised by the participants prior to the workshop included:

- 1) Can fully Bayesian method be developed and practically implemented? In the case of ensemble methods, the main difficulty seems to be the large dimension of atmospheric and ocean models, which have so far been prohibitive for algorithms such as particle filters;
- 2) Ensemble estimation, which aims at defining probability distribution, is of a different nature than deterministic estimation, which aims at determining a point estimate. What are the ways for properly evaluating ensemble estimation?
- 3) Model errors, and different types of observational errors too, are certainly correlated in time. Sequential assimilation cannot be optimal in the presence of time-correlated errors. What are the ways to deal with temporal correlation?;
- 4) Turbulence is associated with complex interaction between spatial scales. What is the impact of those interactions on assimilation? For instance, is it possible to reconstruct the small scales of the motion from observations of the large scales?

In Section ?? we summarize the progress made during this workshop.

3 Workshop Presentations

This section presents a short summary of the presentations made during the workshop. The presentations themselves are available online at <http://kayo.bol.ucla.edu/birs/>.

3.1 Atmospheric Data Assimilation

Andrew Lorenc *“Research Issues in Data Assimilation for Operational NWP”*

Operational NWP has improved predictive skill by about a day per decade since the 1970s. Much of this is due to four-dimensional data assimilation methods, which fit the best available numerical forecast model to observations, allowing for the error characteristics of both. Statistically based methods are needed because observations, although plentiful in the satellite era, are incomplete and relatively inaccurate, compared to the information carried forward by a good forecast model from past observations.

Variational methods use Gaussian models to characterise the errors in the forecasts and observations; the cost and complexity of good forecast models means that the true errors are unknowable. Error modelling assumptions are essential, and the Gaussian assumption leads to computationally tractable linear systems. Recently, in order to continue to improve, it has become necessary to allow for the flow dependence of forecast errors. Statistically based four-dimensional variational methods (4D-Var) are used in most of the best synoptic-scale NWP systems, while ensemble methods for characterising errors are increasingly important. Another issue topic is the modelling of the effect of forecast model errors, rather than initial condition errors, on forecast errors. The development of these methods is the subject of much current research.

Gaussian assumptions, with a linearisable forecast model, lead to methods related to the Kalman filter (KF). Although the KF itself is not affordable, its linear equations enable approximations such as 4D-Var and the Ensemble KF which are feasible even for complex NWP models; it is likely that operational NWP will be based on such methods for some time. Nevertheless nonlinear relationships and the related non-Gaussian distributions are important; methods must be adapted to perform well in such cases (sometimes in an ad hoc way). One possible consequence of nonlinearity is that the Kalman filter ‘blows up’ if there are chaotic features which are so poorly observed that they remain chaotic in the assimilation system. This can happen in the upper stratosphere, and will happen in a global convective-scale model. In the real world, and in realistic nonlinear models, there is a climate attractor. Nonlinear processes damp perturbations (from the climate mean state) which are large compared to the climate variability. In the Kalman filter, and in the linear models used in 4D-Var, this damping needs to be added explicitly. Another consequence of this attractor is the existence of coherent structures such as fronts, inversions and cyclones. Forecasts often have plausible structures, in the wrong place. This can lead to a significantly non-Gaussian and biased error distributions. Adaptations include the incremental approach and nonlinear initialisation. Much harder to deal with is a model with errors which mean its attractor does not match the atmosphere’s.

Increases in computer power mean we can now develop convective-scale NWP systems; a major challenge is to extend the above approaches. Except perhaps in limited regions with good Doppler radar coverage, nonlinear effects will be more important; we need to spin-up realistic convective cells which match available observations. Luckily for our ability to make forecasts, convection is often largely determined by larger-scale and topographic forcings, so multi-scale assimilation methods are needed which preserve large-scales from an optimal global system, while still fitting detailed observations when they exist.

Pierre Gauthier *“Mathematical Problems Associated with Atmospheric Data Assimilation and Weather Prediction”*

The duality principle presented by Courtier (1997) states that the 3D-Var and the Physical-Space Analysis System (PSAS) (or dual form) are just different algorithms to solve the same problem. It was also shown that the two algorithms with their own specific preconditioning can be expected to converge at a similar rate as their Hessian matrices have the same condition number. A 4D-Var algorithm being merely an extension of 3D-Var, the so-called 4D-PSAS should also be equivalent. In this presentation, results will be presented to establish the equivalence of the two approaches. To tackle the nonlinear problem, an incremental formulation is introduced and the equivalence will be established to stress the role of the outer loop process. Results from El Akkraoui *et al.* (2008) indicate some convergence problems that were encountered with the dual form. Moreover, when cycling an assimilation system, the Hessian from the previous minimization can be used to precondition the next assimilation. This is beneficial but cannot be done as easily in a PSAS system. An approach is proposed that takes advantage of the equivalence between the eigenvectors of the dual and primal problems. The interest of the dual form is motivated by the fact that it permits to compute the observation impact through adjoint sensitivities with respect to observations (Langland, 2004). An intercomparison experiment is being carried out at the moment to assess the robustness of the method when used at different

NWP centres. Finally, the weak-constraint 4D-Var can also be formulated in either its primal or dual form, the latter having the advantage of using a control variable with a considerably lower dimension. This avenue is now being examined in the context of a simplified barotropic model.

Joint with Amal El Akkraoui, Simon Pellerin and Samuel Buis.

3.2 Oceanic Data Assimilation

Robert N. Miller “*Estimation of Representation Error in Ocean Models*”

Much of the variability in the observed data arises from physical causes that are often neglected in ocean general circulation models (GCMs). Models that are commonly used as components of climate models or coupled to models of ocean ecology are implemented with resolution too coarse to resolve western boundary currents or eddies, so signals present in the observed data resulting from these phenomena cannot be usefully assimilated. That part of the variability contributes to the model-data misfits and must be treated as error. It is therefore referred to as ‘representation error’, since the physics of the model are inadequate to represent it.

We describe the construction of a static optimal interpolation scheme based on projection of the model-based misfits into the space whose variability can be reliably simulated by a common non-eddy resolving GCM applied to the north Pacific ocean, and use our scheme to assimilate remotely-sensed SST observations. Most of the correction to the model run appears in regions where the model output is reliable. Correction is minimal in the Kuroshio. Our method for calculating the forecast error covariance allows us to explicitly estimate of the statistics of the representation error.

We also present an ensemble calculation to show that our error estimates are sufficient to produce ensembles with statistical properties that are similar to the model-data misfits. Similar error estimate could be used to implement an ensemble Kalman filter that would account for representation

Zhijin Li “*Development of Data Assimilation Schemes in Support of Coastal Ocean Observing Systems*”

The Integrated Ocean Observing System (IOOS) is an emerging national program, whose goal is to develop and sustain a network of integrated coastal and ocean observations. One major component of IOOS is the Regional Coastal Ocean Observing Systems (RCOOSs). For RCOOSs, a real-time data assimilation and forecasting system has been considered as an integrated component. We have developed a three-dimensional data assimilation (3DVAR) scheme in association with the Regional Ocean Modeling System (ROMS) in support of coastal ocean observing systems. The formulation is described, and several challenges are addressed. The major challenges are those related to complexity of topography, uncertainties of atmospheric and fresh water runoff forcing, and observability.

Joint with Yi Chao, James C. McWilliams, Kayo Ide

Keith Thompson “*Predicting Mesoscale Variability of the North Atlantic Using a Simple Physically Motivated Scheme For Assimilating Altimeter and Argo Data*”

A computationally-efficient scheme is described for assimilating sea level measured by altimeters and vertical profiles of temperature and salinity measured by Argo floats. The scheme is based on a transformation of temperature, salinity and sea level into a new set of physically-motivated variables for which it is easier to specify spatial covariance functions. The scheme allows for sequential correction of temperature and salinity biases, and online estimation of time-dependent background error covariance parameters. Two North Atlantic application, both focused on predicting mesoscale variability, are used to assess the effectiveness of the scheme. In the first application the background field is a monthly temperature and salinity climatology and skill are assessed by how well the scheme can recover Argo profiles that have not been assimilated. In the second application the backgrounds are forecasts made by an eddy permitting model of the North Atlantic. Skill is assessed by the quality of forecasts with lead times of 1 to 60 days. For both applications it is shown that the scheme has useful skill. The benefits of using physical constraints to reduce the computational cost of assimilation is discussed in general, and compared to other cost-reducing approaches such as those used in the SEEK filter.

Joint with Yimin Liu

3.3 Variational Method

Mark Buehner “*Towards an Improved Use of Flow-Dependent Background Error Covariances in a Variational Data Assimilation System*”

Since early 2005, Environment Canada has been operationally running both a global four-dimensional variational analysis system (4D-Var) and an ensemble Kalman filter (EnKF). Both systems employ the same atmospheric model though with different spatial resolution. The co-existence of these two operational systems at a numerical weather prediction (NWP) centre provides a unique opportunity. In this talk approaches for incorporating background-error covariances estimated from the EnKF ensembles in the variational assimilation system are discussed. The techniques of spatial and spectral localization are briefly described and demonstrated with a simple one-dimensional problem. Then, the impact of localizing ensemble-based covariances in the variational system are shown. The practical challenge of simultaneously applying localisation in both spectral and spatial domains within a realistic NWP data assimilation system is also presented.

Ricardo Todling “*Catching up to the World: The GMAO 4d-Var and its Adjoint-Based Tools*”

The fifth generation of the Goddard Earth Observing System (GEOS-5) Data Assimilation System (DAS) is a 3d-var system that uses the Grid-point Statistical Interpolation (GSI) system developed in collaboration with NCEP, and a general circulation model developed at Goddard, that includes the finite-volume hydrodynamics of GEOS-4 wrapped in the Earth System Modeling Framework and physical packages tuned to provide a reliable hydrological cycle for the integration of the Modern Era Retrospective-analysis for Research and Applications (MERRA). This MERRA system is essentially complete and the next generation GEOS is under intense development. A prototype next generation system is now complete and has been producing preliminary results. This prototype system replaces the GSI-based Incremental Analysis Update procedure with a GSI-based 4d-var which uses the adjoint of the finite-volume hydrodynamics of GEOS-4 together with a vertical diffusing scheme for simplified physics. As part of this development we have kept the GEOS-5 IAU procedure as an option and have added the capability to experiment with a First Guess at the Appropriate Time (FGAT) procedure, thus allowing for at least three modes of running the data assimilation experiments.

The prototype system is a large extension of GEOS-5 as it also includes various adjoint-based tools, namely, a forecast sensitivity tool, a singular vector tool, and an observation impact tool, that combines the model sensitivity tool with a GSI-based adjoint tool. These features bring the global data assimilation effort at Goddard up to date with technologies used in data assimilation systems at major meteorological centers elsewhere.

Joint with Yannick Trémolet

Nancy Nichols “*Use of Reduced Order Models in incremental Four-Dimensional Variational Data Assimilation*”

Incremental methods used operationally for 4D-variational data assimilation aim to solve a sequence of linear approximations to the full nonlinear problem. These methods consist of inner iteration loops for solving each linear approximation via an adjoint procedure and an outer iteration loop in which the nonlinear analysis is updated and the problem is re-linearized about the current estimate of the analysis. In order to increase the computational efficiency of these methods, low rank approximations to the inner linear systems are used, thereby reducing the work needed in each inner iteration loop. Low resolution models derived from spatial or spectral truncations of the full system commonly provide the reduced rank approximations. Convergence of these procedures depends on how accurately the low order models approximate the full system model.

New techniques for finding reduced rank models based on balanced truncation methods developed for large scale control system design are presented here with application to the incremental 4D-Var procedure. Reduced models determined by these methods are optimal in the sense of producing the best match to the frequency response of the full system. More of the dynamical information of the full system is therefore retained by these reduced models than by a low resolution system. Results obtained for simple shallow water test cases illustrate the superior performance of these reduced models and show that the same accuracy in the analysis can be obtained more efficiently with a much lower dimensional reduced order approximation than with a low resolution model.

Joint with Amos S. Lawless, Caroline Boess, Angeliza Bunse-Gester

3.4 Ensemble-Based Method

Martin Ehrendorfer “*Ensemble-Based Data Assimilation*”

Ensemble-based data assimilation methods related to the fundamental theory of Kalman filtering have been explored in a variety of mostly non-operational data assimilation contexts over the past decade with increasing intensity. While promising properties have been reported, a number of issues that arise in the development and application of ensemble-based data assimilation techniques, such as in the basic form of the ensemble Kalman filter (EnKF), still deserve particular attention.

The necessity of employing an ensemble of small size represents a fundamental issue which in turn leads to several related points that must be carefully considered. Attempts to reduce effectively the sampling error due to small ensembles and at the same time maintaining an ensemble spread that realistically describes error structures has led to the development of variants of the basic form of the EnKF. In this presentation, several of the above-mentioned issues are discussed and illustrated together with a brief review of the methodology that has been developed by varying the basic form of the EnKF.

Zoltan Toth “*Towards an Improved Use of Flow-Dependent Background Issues Related to the Use of Ensembles in Data Assimilation and Targeting*”

The assimilation of observations into numerical models of dynamical systems ideally builds on both dynamical and statistical principles. The presentation focus is on the interface between dynamics and statistics, exploring some aspects from both fields that may either be critical, or could possibly be compromised for achieving a balanced solution, leading to successful data assimilation (DA). Questions and issues explored include: The role of a numerical first guess in traditional and ensemble-based DA; Alternative ways of generating first guess fields for ensemble-based DA; Statistical and dynamical considerations when estimating the background error covariance; How to assimilate data with an imperfect model? Can information from highly non-linear forecasts be used for targeting observations to improve such forecasts? What other issues one must consider for an integrated observing, data assimilation and forecast system for chaotic systems?

Joint with Malaquias Pena, Mozheng Wei, Yucheng Song

Istvan Szunyogh “*Flow Dependence of the Performance of an Ensemble Based Analysis-Forecast System*”

Data assimilation is a problem at the intersection of dynamical systems theory and mathematical statistics. In this talk, we focus on the dynamical systems aspects of the problem. In particular, we argue that most techniques of dynamical systems theory, which have already been applied to geophysical fluid dynamical systems, have a solid theoretical foundation only for low-dimensional systems. Since geophysical fluid dynamical systems are inherently high-dimensional, a systematic approach to extend the theoretical machinery to increasingly more complex systems would be highly desirable. In this talk, we outline one potential approach to address this issue: the high-dimensional system is viewed as the collection of local systems; the local state vector is defined by the variables of the original high-dimensional system from a local neighborhood of each physical location; and properties that smoothly vary with the location are computed based on the local state vectors. We illustrate this approach by using it to explain the spatio-temporal variability of the performance of an ensemble-based analysis-forecast system. This system consists of the Local Ensemble Transform Kalman Filter data assimilation scheme and a reduced resolution version of the model component of the Global Forecast System of the National Centers for Environmental Prediction.

Eric Kostelich “*Recent Results of the 4D Local Ensemble Transform Kalman Filter (4D-LETKF)*”

I outline the latest results of the Maryland/ASU implementation of the Local Ensemble Transform Kalman Filter (LETKF) to the Global Forecast System of the National Centers for Environmental Prediction (NCEP). Measures of forecast accuracy and comparison with with operational NCEP analyses are described. The computational efficiency of our implementation of the LETKF also is assessed, including issues of scaling, load balancing, and data transport.

3.5 Hybrid Methods

Fuqing Zhang “*Coupling Ensemble Kalman Filter with Four-Dimensional Variational Data Assimilation*”

This study examines the performance of coupling deterministic four-dimensional variational assimilation

(4D-VAR) with an ensemble Kalman filter (EnKF) to produce a superior hybrid approach for data assimilation. The coupled assimilation scheme (E4D-VAR) benefits from using the state-dependent uncertainty provided by EnKF while taking advantage of 4D-VAR in preventing filter divergence. The 4D-VAR analysis produces posterior maximum likelihood solutions through minimization of a cost function about which the ensemble perturbations are transformed, and the resulting ensemble analysis can be propagated forward both for the next assimilation cycle and as a basis for ensemble forecasting. The feasibility and effectiveness of this coupled approach are demonstrated in an idealized model with simulated observations. It is found that the E4D-VAR is capable of outperforming both 4D-VAR and the EnKF under both perfect- and imperfect-model scenarios. The performance of the coupled scheme is also less sensitive to either the ensemble size or the assimilation window length than that for standard EnKF or 4D-VAR implementations.

Joint with Meng Zhang, James A. Hansen

3.6 Observations

Gérald Desroziers “*Use of Observations in Data Assimilation Schemes*”

Modern operational data assimilation schemes rely on the use of a large range of types of observations. This is made possible via the implementation of observation operators that allow to go from model space to observation space and that especially permit the direct assimilation of satellite radiances. Because most data assimilation schemes rely on the theory of estimation, they also have a need to diagnose and specify observation error covariances. Some observations, such as satellite data, are known to be biased. In that case, a particular procedure such as variational bias correction has to be implemented. Interestingly, ensembles of perturbed assimilations are classically based on a perturbation of observations. Such ensembles allow to document background error covariances that are a key ingredient in a data assimilation scheme. On another hand, the variances given by such ensembles have most often to be inflated. Such an inflation can be tuned via the comparison of ensemble variances to the variances deduced from statistics of the innovation vector. Other aspects are discussed such as the different ways to measure the impact of observations on analyses and subsequent forecasts.

Art Krener “*Eulerian and Lagrangian Observability of Point Vortex Flows*”

We study the observability of one and two point vortex flow from one or two Eulerian or Lagrangian observations. By observability we mean the ability to determine the locations and strengths of the vortices from the time history of the observations. An Eulerian observation is a measurement of the velocity of the flow at a fixed point in the domain of the flow. A Lagrangian observation is the measurement of the position of a particle moving with the fluid. To determine observability we introduce the observability and the strong observability rank conditions and compute them for the various flows and observations. We find that vortex flows with Lagrangian observations tend to be more observable than the same flows with Eulerian observations.

We also simulate extended Kalman filters for the various flows and observations and find that they perform poorly when the observability rank condition or the strong observability rank condition fails to hold.

Richard Ménard “*Model Error as an Unobserved Variable: What Do We Know From Estimation Theory*”

Model error can be accounted as an unknown tendency in the dynamics equation. Since most observation operators relate to state variables as opposed to their tendencies, model error can be accounted as an ‘unobserved variable’. Its impact however built up with time. We review several of the known schemes, making the links between variational and Kalman filter and smoother formulations. In a simple model we present some results and discuss the issue observability of the model error estimation problem. Some ideas about the use of lagged innovations to obtain critical error statistics are also presented. Finally, using an information filter formulation, we note some specific properties arise in the estimation of unobserved variable and speculate that it could be used to distinguish it from observation error.

N. Sri Namachchivaya “*Target Detection in Multi-Sensor and Multi-Scale Environments*”

We describe nonlinear filtering in multi-scale environment, dimensional reduction for noisy nonlinear systems, and reduced order nonlinear filters for physically-motivated problems.

3.7 Lagrangian Aspects

Andrew Tangborn “*Assimilation of Vorcore Polar Balloons*”

25 long lived constant volume stratospheric balloons were flown over Antarctica from September 2005 - January 2006. They produced position, pressure and temperature data every several minutes. Wind vectors were derived from the position measurements. We present the results of assimilating Vorcore balloon winds into the GEOS-4 data assimilation system. Improvements to the wind field are found by comparing with an independent data set. The analyzed winds are used to transport ozone fields during the same period in the GMAO ozone assimilation system. Modest improvements to the ozone forecasts are found. We also discuss current plans for assimilation in the GEOS-5 assimilation system and the upcoming Concordiasi balloon campaign.

Kayo Ide “*Lagrangian Data Assimilation: Method and Mathematical Issues*”

The Lagrangian data assimilation (LaDA) is a method for the direct assimilation of Lagrangian observations. Lagrangian instruments in the oceans, such as drifters and floats, are often designed to sample ocean properties while remaining on a two-dimensional surface in the three-dimensional ocean except when descending to or ascending from the desired depth. By augmenting the model state vector with the coordinates of the instruments, the LaDA can assimilate the Lagrangian positions without the need for any commonly used approximations to transform Lagrangian observations into Eulerian (i.e., velocity) observations.

We describe the LaDA method and the observing system design for optimal deployment of Lagrangian instruments. Using the judicious design of the deployment strategy, the LaDA is strikingly efficient in tracking the local coherent structures, such as ocean eddies, as well as estimating the large-scale ocean circulation.

Joint with Guillaume Vernières, Chris Jones

Guillaume Vernières “*Lagrangian Data Assimilation: Application to Gulf of Mexico*”

We demonstrate effectiveness of LaDA in a realistic setting for ocean-eddy tracking in Gulf of Mexico. We evaluate three types of observations for ocean eddy tracking: the measurement of velocities at fixed station, the horizontal position of surface drifters, and the three dimensional position of isopycnal floats. By considering the “volume of influence”, we examine how and to what extent the LaDA propagates the information vertically to estimate the three-dimensional ocean structure. We show that as little as one judiciously placed drifter or isopycnal float is needed to recover an eddy being shed by the loop current.

Joint with Kayo Ide, Chris Jones

3.8 Bayesian Approaches and Non-Gaussianity

Peter Jan van Leeuwen “*Particle Filtering in Large-Scale Systems: Problems & Potential Solutions*”

Starting from Bayes theorem, it is shown how the Kalman filter and 4D-Var can be derived. Then we concentrate on methods that use a particle representation of the model probability density function (pdf). The Ensemble Kalman Filter (EnKF) is derived, and we shortly touch upon the Ensemble Kalman Smoother. For applications in large-scale problems the number of particles is limited to typically 10-100 because of computational limitations. Given the number of independent unknowns, of the order of 1 million, the ensemble size is way too low. In that case the general formulation does not work, and adjustments have to be made. One of them is to do the analysis locally, i.e., use only observations close to a certain gridpoint to determine the analysis there. This procedure increases the effective ensemble size by a substantial factor, sometimes a factor 1000. While this is still too low, first-order statistics can be determined with reasonable accuracy. A serious drawback is that the EnKF assumes that the pdf is Gaussian, which can be bad for strongly nonlinear systems. In that case a so-called particle filter can be used in principle, in which the analysis consists of weighting the particles according to their ‘distance’ to the observations (importance weighting/sampling). Again, the affordable number of particles is too low for most geophysical applications. The localization cannot be applied directly in the particle filter, because it tends to break local geophysical balances, so other solutions have to be found. We discuss several possibilities, such as reduced-space solutions, merging particle filters, marginal pdf’s, localization guided by the EnKF etc. Although all these ideas have potential, the final answer is still to be found.

Chris Snyder “*Obstacles to Particle Filtering in High Dimensions*”

Particle filters are ensemble-based assimilation schemes that, unlike the ensemble Kalman filter, employ a fully nonlinear and non-Gaussian analysis step. Evidence is presented that, if the observation log-likelihood has an approximately Gaussian distribution, the ensemble size required for a successful particle filter scales exponentially with the variance of the observation log-likelihood, rather than the state dimension per se. Asymptotic results, following the work of Bengtsson, Bickel and collaborators, are provided for two cases: one in which each prior state component is independent and identically distributed, and one in which both the prior pdf and the observation errors are Gaussian. I also discuss ‘effectively low dimensional’ situations in which the observation log-likelihood is far from Gaussian despite large state dimension and large numbers of observations.

Mike Dowd “*Sequential Monte Carlo Approaches for Parameter and State Estimation*”

Statistical methodologies for estimating state and parameters for time dependent stochastic dynamic systems are now well established. For nonlinear dynamics and non-Gaussian observations these data assimilation approaches rely on Monte Carlo solutions implemented via particle or ensemble methods. In this talk, I overview new developments in such state estimation methods which rely on resampling/bootstrap and MCMC (or combinations thereof). The associated parameter estimation problem for nonlinear stochastic DE based numerical models is also considered using likelihood and state augmentation approaches. Simple toy models of ocean biogeochemistry using non-Gaussian ecological measurements from a coastal ocean observatory are used for illustration throughout. Challenges for adaptation to data assimilation in large dimension PDE based systems are discussed.

Christopher K.R.T. Jones “*Bayesian Approach to Lagrangian Data Assimilation*”

Lagrangian data arise from instruments that are carried by the flow in a fluid field. Assimilation of such data into ocean models presents a challenge due to the potential complexity of Lagrangian trajectories in relatively simple flow fields. We adopt a Bayesian perspective on this problem and thereby take account of the fully nonlinear features of the underlying model. In the perfect model scenario, the posterior distribution for the initial state of the system contains all the information that can be extracted from a given realization of observations and the model dynamics. We work in the smoothing context in which the posterior on the initial conditions is determined by future observations. This posterior distribution gives the optimal ensemble to be used in data assimilation. The issue is then sampling this distribution. We develop, implement, and test sampling methods, based on Markov-chain Monte Carlo (MCMC), which are particularly well-suited to the low-dimensional, but highly nonlinear, nature of Lagrangian data. We compare these methods to the well-established ensemble Kalman Filter (EnKF) approach. It is seen that the MCMC based methods correctly sample the desired posterior distribution whereas the EnKF may fail due to infrequent observations or nonlinear structures in the underlying flow.

Joint with Amit Apte, Andrew Stuart

3.9 Nonlinearity, Non-Gaussianity, and Multi-Scaleness

Marc Bocquet “*Non-Gaussian Data Assimilation: Application to Inverse Modelling of Atmospheric Tracers*”

On the practical side, the goal of this talk is to demonstrate that data assimilation techniques can be used to identify the source of an accidental release of pollutant into the atmosphere, and forecast (possibly in real-time) the subsequent dispersion plume. On the methodological side, the aim is to show that there are circumstances when the use of non-Gaussian techniques in data assimilation is profitable.

A first method is based on the principle of maximum entropy on the mean and briefly reviewed. A second approach, which has not been applied in this field yet, is based on an exact Bayesian approach, through a maximum *a posteriori* estimator. The methods share common grounds, and both perform equally well in practice. When specific prior hypotheses on the sources are taken into account such as positivity, or boundedness, both methods lead to purposefully devised cost-functions, thanks to non-linear convex analysis. These cost-functions are not necessarily quadratic because the underlying assumptions are not Gaussian. As a consequence, several mathematical tools developed in data assimilation on the basis of quadratic cost functions in order to establish *a posteriori* analysis, need to be extended to this non-Gaussian framework.

Concomitantly, the second-order sensitivity analysis needs to be adapted, as well as the computations of the averaging kernels of the source and the errors obtained in the reconstruction. All of these developments are applied to a real case of tracer dispersion: the European Tracer Experiment (ETEX). Examples are also given on the Chernobyl accident. Comparisons are made between a least squares cost function (similar to 4DVar) approach and a cost function which is not based on Gaussian hypotheses. Besides, the information content of the observations which is used in the reconstruction is computed and studied on the application case.

Alternatively these methods can be interpreted as weakly constrained 4DVar-like approaches with a non-Gaussian formalism for model error. Here, model error would be the pollutant source field, which is very uncertain but still the main forcing of the plume dynamics. Possible generalizations of these methods to non-linear physics are sketched.

Youmin Tang “*Advanced Data Assimilation in Strongly Nonlinear Systems*”

Performance of advanced derivativeless, sigma-point Kalman filter (SPKF) data assimilation schemes in a strongly nonlinear dynamical model is investigated. The SPKF data assimilation scheme is compared against traditional Kalman filters such as extended Kalman filter (EKF) and ensemble Kalman filter (EnKF) schemes. Three particular cases, namely the state, parameter and joint estimation of states and parameters simultaneously, from a set of discontinuous noisy observations were studied.

The celebrated Lorenz model with highly nonlinear condition is used as the test bed for data assimilation experiments. The results of SPKF data assimilation schemes were compared with those of traditional EKF and EnKF where a highly nonlinear chaotic case is studied.

Tomislava Vukicevic “*Analysis of the Impact of Model Nonlinearities, Modeling Errors and Gaussian Prior in Inverse Problem Solving*”

In this study, the relationship between nonlinear model properties and inverse problem solutions is analyzed using a numerical technique based on the inverse problem theory formulated by Mosegaard and Tarantola. According to this theory, the inverse problem and solution are defined via convolution and conjunction of probability density functions that represent stochastic information obtained from the model, observations and prior knowledge in a joint multidimensional space. This theory provides an explicit analysis of the nonlinear model function, together with information about uncertainties in the model, observations, and prior knowledge through construction of the joint probability density, from which marginal solution functions can then be evaluated. The numerical analysis technique derived from the theory computes the component probability density functions in discretized form via a combination of function mapping on a discrete grid in the model and observation phase space, and Monte-Carlo sampling from known parametric distributions.

The efficiency of the numerical analysis technique is demonstrated through its application to two well known simplified models of Atmospheric physics: Damped oscillations and Lorenz’ 3-component model of dry cellular convection. The major findings of this study are:

- Use of a non-monotonic forward model in the inverse problem gives rise to the potential for a multimodal posterior pdf, the realization of which depends on the information content of the observations, and on observation and model uncertainties,
- Cumulative effect of observations, over time, space or both, could render unimodal final posterior pdf even with the non-monotonic forward model,
- A greater number of independent observations are needed to constrain the solution in the case of a non-monotonic nonlinear model than for a monotonic nonlinear or linear forward model for a given number of degrees of freedom in control parameter space,
- A nonlinear monotonic forward model gives rise to a skewed unimodal posterior pdf, implying a well posed maximum likelihood inverse problem,
- The presence of model error greatly increases the possibility of capturing multiple modes in the posterior pdf with the non-monotonic nonlinear model, and
- In the case of a nonlinear forward model, use of a Gaussian approximation for the prior update has a similar effect to an increase in model error, which indicates there is the potential to produce a biased mean central estimate even when observations and model are unbiased.

Milija Zupanski “*Dynamical Approach to Nonlinear Ensemble Data Assimilation*”

We present an overview of ensemble data assimilation methods by focusing on their approach to nonlinearities. This subject is introduced from the dynamical, rather than a typical statistical point of view. As such, most problems in ensemble data assimilation, and in data assimilation in general, are seen as means of producing an optimal state that is in dynamical balance, rather than producing a state that is optimal in a statistical sense. Although in some instances these two approaches may produce the same results, in general they are different. Details of this difference are discussed, and also related to variational data assimilation.

Nonlinearities are of special interest in realistic high-dimensional applications, which implies the need for considering the number of degrees of freedom. The means for increasing the degrees of freedom in ensemble data assimilation are briefly discussed, in particular their impact on dynamical balance.

An algorithm named the Maximum Likelihood Ensemble Filter (MLEF) is presented as a prototype nonlinear ensemble data assimilation method. Some results with the MLEF are shown to illustrate its performance, including the assimilation of real observations with the Weather Research and Forecasting (WRF) model for the hurricane Katrina.

Olivier Pannekoucke “*Background Error Correlation Modeling: Representation of the Local Length-Scale From (small) Ensemble*”

Ensembles of perturbed assimilations and forecasts are now a well known method. They mimic the time evolution of the dispersion of possible states in model space. However this method is costly and only a few assimilations can be computed. The issue of how to extract some robust information from an ensemble is discussed. In a first part, some features about background error correlation functions are reminded. In particular, it is shown how diagnoses of local correlation length-scale can illustrate the geographical variations of correlation functions. A second part of the talk is focused on the representation of geographical variations through the wavelets diagonal assumption. In particular, some interesting properties of this formulation are illustrated: it allows the representation of length-scale variations, and it offers interesting filtering properties. The last part of the talk deals with an alternative way to represent geographical variations of correlation functions via a modelisation based on the diffusion equation.

Joint with Loïk Berre, Gérald Desroziers, Sébastien Massart

3.10 Future Perspectives

Olivier Talagrand “*A Few Future Perspectives for Assimilation*”

A number of questions relative to the theory and practice of assimilation are discussed. Particular emphasis is put on ensemble and assimilation validation criteria. Validation requires comparison with unbiased *independent observations* that have not been used in the assimilation. For ensembles, reliability and resolution are key elements. One element that needs to be considered in data assimilation is the presence of observation and model errors that may be correlated in time. Time-correlated errors cannot be taken into account in sequential schemes that discard observations as they are used. 4D-Var and smoother schemes can take into account errors that are correlated in time. Is it possible to develop fully Bayesian algorithms for systems with dimensions encountered in meteorology and oceanography? Would that require totally new algorithmic developments? Finally, the objective evaluation of an assimilation system raises a number of questions to extend notions of information content to the general nonlinear case. Estimation of the first and second order moments of observation errors is needed but current observations may not be sufficient to fully characterize them. Given all those limitations, one could ask instead how to make the best of an assimilation system.

4 Summary of Scientific Progress

The objective of this workshop was to explore and discuss areas and specific problems in which collaborative efforts with the mathematical community could help to address fundamental and challenging issues in data assimilation. The BIRS workshop brought together practioners of data assimilation with mathematicians and statisticians for a period of time and at a place where the intensive focus and energy could serve to define the

way forward. It offered a unique and much needed opportunity to go beyond what we were able to achieve in the previous programs. The outcome of the workshop is expected to lead to significant contributions to geophysical DA through the development of new statistical, dynamical and computational strategies.

During the workshop, several mathematical issues were raised and discussed. Those relate to current problems that need to be investigated to make advances in data assimilation methodology in support of atmospheric and oceanic modeling.

4.1 Addressing and accounting for uncertainties

The statistical estimation problem necessitates the characterization, representation and estimation of uncertainties within the assimilation. It would also be important to relax some of the constraints embedded within the current assimilation systems:

1. *Non-gaussianity in probability density function of the state*: linearity and Gaussianity still underlie most assimilation systems. There is evidence that these assumptions are not verified in many cases. However, the extension to the non-Gaussian p.d.f. brings up many difficulties regarding the modeling of the probability distributions and their estimation. From a practical point of view, the question is then to know whether it is at all possible to develop fully Bayesian algorithms for systems with large dimensions such as those encountered in meteorology and oceanography.
2. *Sampling*: ensemble-based methods are using ensembles of finite-size and this raises some questions about the *optimal* sampling of a non-Gaussian pdf in large dimensional spaces while preserving dynamical constraints.
3. *Representation of model errors*: most assimilation methods assume that the forecast error can be explained by errors in the initial conditions. It is important to take into account the fact the model itself contains error. This includes systematic and random error which is correlated in time.
4. *Algorithmic issues*: large scale problems present algorithmic difficulties that must be addressed. This is a concern for minimization algorithms used in variational forms of data assimilation. Optimal sampling of a phase-space of large dimensions is not so obvious particularly when the underlying p.d.f. is unknown. Assimilation algorithms also involve linear algebra problems such as singular value decomposition, generalized inverse, etc. Finally, efficient nonlinear solvers are needed as well in the more general Bayesian formulation.

4.2 Mathematical issues in (geo)physical systems

1. *Physical balance vs. localization, large-dimension, high-resolution*: geophysical systems are constrained by the dynamical laws that govern them. This leads to some *balance constraints* that are approximately imposed. Although large scale constraints like quasi-geostrophy have been imbedded within the formulation of background-error covariances for a long time, dynamical constraints are not so well known for smaller scale dynamics. In ensemble systems, it is often necessary to “localize” and, in this case, how to impose balance constraints remains an open question.
2. *Scale interactions*: the current thinking is that the evolution of the small scales is to a great extent determined from the large scale part of the flow. Although a simple downscaling of the large scales may capture most of the details of the flow, the scale interactions need to be better understood to adequately represent the influence of the small scales on the large scales.
3. *Parameter estimation in very large dimensional systems*: in meteorology, data assimilation focuses mainly on the analysis of the initial conditions. However, in several applications, it would be more important to determine some unknown parameters that define the system. In atmospheric chemistry for instance, sources and sinks of pollutants are far more important than the initial distribution of the chemical species. Parameterizations schemes are used to represent subscale processes which also involve a number of parameters that are often determined by “tuning” the system. Parameter estimation would then seek to estimate such parameters and the associated estimation error.

4. *Observability*: the volume of meteorological observations is fairly large but this is not the case for oceans. Atmospheric chemistry also requires observations of numerous chemical species which are not observed. This puts some limitations on the estimation of the different error sources (e.g., observation, model, background). The volume of observations that is needed depends on the dynamical couplings and constraints of the systems which may reduce the dimensionality of the problem. The volume of available observations then puts some limitations on the estimation of the state of the atmosphere and its variability.

4.3 Incorporating ideas from mathematics

From the summary presented above, some directions emerge in which mathematical ideas could help to address key problems. The evolution of the atmosphere and the oceans is governed by dynamical systems which embeds the balance constraints and processes acting on different spatial and temporal scales. How to tackle the problems associated with multiscale phenomena can then be cast in terms of the theory of dynamical systems. Can the dynamical constraints be used to reduce the dimension of the problem. For example, dynamical systems provided a framework in which the onset of instabilities could be reduced to systems of low dimensions (center manifold theorem).

Data assimilation and ensemble prediction already use concepts of information theory to evaluate the information content of observations. However, this relies on some assumptions that are not respected for nonlinear systems. Any progress made on extending ideas of information theory to nonlinear systems and non-Gaussian p.d.f. could be most useful.

Finally, in presence of model error, current assimilation algorithms are faced with algorithmic problems given the computing load they involve. Variational assimilation relies on iterative algorithms that are not well suited for massively parallel architectures. Would it be possible to design new algorithms, exploring more than one dimension at the time? This could be cast in some hybrid form of variational ensemble data assimilation to move away from purely sequential schemes that is at the heart of ensemble Kalman filtering. This may also give rise to problems that would require nonlinear solvers.

5 Dissemination of the Outcome of the Workshop

The organizers and participants to this workshop express our sincere appreciation to the Banff International Research Station for hosting and supporting this exciting and fruitful event. The outcome of this workshop will be disseminated as follows:

Two meeting reports are planned to the society bulletin for both the atmospheric/oceanic community and the mathematical community.

1. *Bulletin of the American Meteorological Society (BAMS)*: This report targets scientists who are actively involved in data assimilation. This exposes the scientists to the new directions and development in data assimilation made possible by the means of mathematics. P. Gauthier and K. Thompson (organizers of the workshop) lead this report.
2. *Society for Industrial and Applied Mathematics (SIAM) News*: This report targets mathematicians who are not currently working on data assimilation yet but are experts on the related areas of mathematics. This stimulates the mathematicians to contribute to advancement of data assimilation. K. Ide and C.K.R.T. Jones (organizers) lead this report.

A special issue of the collections of papers based on this workshop in one of the leading journals on data assimilation, *Monthly Weather Review (MWR)*, published by the American Meteorological Society. K. Ide (Organizer) and F. Zhang (participant, editor of MWR) are the co-editors of this special issue.