Reanalysis: Data Assimilation for Scientific Investigation of Climate

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1 Introduction

Reanalysis is the assimilation of long time series of observations with an unvarying assimilation system to produce datasets for a variety of applications; for example, climate variability, chemistry-transport, and process studies. Reanalyses were originally proposed for atmospheric observations as a method to generate "climate" datasets from "weather" observations. As the satellite records of chemical, land and oceanic parameters build with time, "reanalyses" are being developed for other types of observations. Coupled reanalyses, for example atmospheric-ocean reanalyses, are possible. In addition, very long reanalyses that use no satellite observations are being planned (*e.g.* Compo *et al.* 2006). Reanalysis datasets have become one of the most important datasets for scientific and application communities. As of July 2009, the Kalnay *et al*. (1996) paper, which describes one of the first reanalysis datasets, has more than 6600 recorded citations. In this chapter discussion will be drawn from the experience of atmospheric reanalysis, and the issues raised are relevant to all types of reanalysis.

The provision of reanalyses was advocated by Bengtsson and Shukla (1988) and Trenberth and Olson (1988) in order to provide homogeneous datasets for climate applications and to encourage research in the use of satellite observations without the operational constraints of Numerical Weather Prediction. Trenberth and Olson (1988) calculated derived products, such as the Hadley circulation, from assimilation analyses used in operational weather forecasting. They found large discontinuities in time series of these derived quantities. The discontinuities were clearly linked to changes in the assimilation system, such as changes in the forecast model. Given the four-dimensional (time and space) nature of assimilated datasets and the success of assimilation in providing initial conditions for weather forecasting, it was logical to propose using a single, non-varying assimilation system to generate a long time series for the purpose of investigating the Earth's climate.

Kalnay and Jenne (1991) proposed that a reanalysis be performed as a partnership between the National Meteorological Center (NMC, now part of the National Centers of Environmental Prediction, NCEP) and the National Center for Atmosphere Research (NCAR). This project required the preparation of the input datasets, the definition of the analysis system, and a data distribution plan. The analysis system was a version of the operational system used for weather prediction, but at lower resolution.

Three organizations performed a first generation of reanalyses in the spirit of Bengtsson and Shukla (1988) and Kalnay and Jenne (1991). Aside from the NCEP/NCAR reanalysis (Kalnay *et al*. 1996), the European Centre for Medium-Range Weather Forecasts (ECMWF) executed the ERA-15 project (Gibson *et al*. 1997) and the Data Assimilation Office (DAO, now the Global Modeling and Assimilation Office, GMAO) at NASA's Goddard Space Flight Center provided the 17-year Goddard Earth Observing System, Version 1 (GEOS-1) reanalysis (Schubert *et al*. 1993). These three reanalyses have been cited in many studies, which document successes as well as identifying a series of shortcomings that stand at the core of future research. New reanalyses have come from these and additional organizations.

The quality of the first-generation reanalyses is documented in the proceedings from two workshops (WCRP 1998, 2000; see also, Newson 1998). Kistler *et al.* (2001) gives an excellent overview of the NCEP/NCAR reanalysis project, and the discussions in that paper are relevant to all of the projects. Quantities that are directly constrained by the observations, *i.e.*, temperature, geopotential, and the rotational component of the wind, are consistent across the three reanalyses. At the other extreme, quantities that are only weakly constrained by the observations or are dependent upon the physical parametrizations of the assimilating models differ greatly. Further, these derived quantities, which include the divergent component of the wind, precipitation, evaporation, clouds, fresh-water runoff, and surface fluxes, have significant uncertainties, as revealed either by independent validation or through applications in scientific studies.

Following this first set of reanalyses there is a second generation that strives to address some of the deficiencies of the first generation of reanalyses as well as to extend the reanalyses to earlier times. Kanamitsu *et al*. (2002) describe the incremental evolution of the original NCEP/NCAR reanalysis, which was performed in partnership with the United States Department of Energy (hence, NCEP/DOE reanalysis). ECMWF produced a 40 year reanalysis (Uppala *et al*. 2005) with significant incorporations of lessons learned. Both of these reanalyses did benefit from improvements to the assimilation system and from better treatment of the observations. However, there remain in these datasets some deficiencies that are, perhaps, intrinsic to reanalysis datasets. These deficiencies are related to the variability of the observational data stream and to the representation of the hydrometeorological and energy cycles. These subjects will be explored in more detail in this chapter. Reanalysis datasets, especially those generated at NASA's GMAO, have been used extensively in constituent transport applications (*e.g.* Bey *et al.* 2001; Douglass *et al.* 2003). Like studies involving the hydrometeorological cycle, constituent transport studies require closed, physically consistent budgets. That is, the reanalysis products need to satisfy fundamental conservation equations. The results from these studies highlight that assimilated datasets do not satisfy conservation principles and, hence, are not physically consistent. The development of physically consistent assimilated datasets remains a research challenge (se chapter *The Role of the Model in the Data Assimilation System*, Rood).

In addition to the extensions of the original reanalysis efforts, there have been new reanalysis efforts. The JRA-25 was generated by the Japan Meteorological Agency and described by Onogi *et al*. (2007). This reanalysis has paid specific attention to improvement of precipitation, and the representation of global precipitation is improved relative to the ERA-40 and NCEP/DOE reanalyses. Mesinger *et al*. (2006) document NCEP's North American Regional Reanalysis (NARR), which is a high resolution regional reanalysis that uses the global reanalysis as the boundary conditions for a regional model-assimilation system.

Recently, first results from two new products were released. These are NASA's Modern Era Retrospective-analysis for Research and Applications (MERRA) and ECMWF's ERA-Interim. (Links are provided at the end of the chapter.) These reanalyses have had significant attention paid to the input data stream, data quality control, bias correction, and the interface between the model and the analysis system. They are designed to address many of the problems discussed below. The first results suggest significant progress has been made.

Trenberth *et al.* (2008b) and Bengtsson *et al.* (2007) summarize the state of the art at the time of this writing and argue for continuing research to improve reanalysis. Based on the successes of reanalysis in climate science, there is broad agreement that the improvement, the extension, and the production of reanalyses are an essential element of the business of climate research. This is a rapidly changing field, with much of the current information found online from institutional and project websites. A snapshot of these activities is given at the end of this chapter to provide an introduction into current information. The chapter will next highlight some of the special aspects of the problem of data assimilation intended to be used in the scientific investigation of climate and constituent transport. This will be followed by sections on hydrometeorological applications of reanalysis and constituent transport applications. Finally, a discussion of the challenges for future reanalysis projects is presented. The references and examples here are expository and by no means comprehensive.

2 Special aspects of the reanalysis problem

This section presents, first, lessons learned from reanalysis activities. Then two related aspects that provide difficult challenges to reanalysis, heterogeneity of the input data stream and bias, are discussed. The impact of data heterogeneity and bias on trends derived from assimilated datasets is then highlighted.

Lessons learned. The lessons learned from the first-generation reanalyses provided the foundation for a second generation of reanalyses. These lessons can be summarized as general success in defining the major modes of variability on synoptic and planetary scales, as well as credible representation of the variability associated with longer-term, large-scale phenomena: *e.g.* monsoons, El Niño – La Niña, and the Madden-Julian oscillation. The deficiencies include fundamental problems in the hydrological cycle and the general circulation as well as artifacts in the reanalysis datasets that are directly related to changes in the observing network. The representation of tropical meteorological features is not as robust as the representation of the middle latitudes. The quality in the Arctic and Antarctic is highly variable (Bromwich *et al.* 2007).

Most of the primary references that describe reanalysis datasets and workshop reports have stated that reanalyses are not appropriate for trend studies (WCRP 1998, 2000; Newson 1998; Kistler *et al*. 2001). This is attributed, first, to the sensitivity of the assimilated dataset to changes in the observing system. Variables that are prescribed by the physical parametrizations are more sensitive to variability in the observing system than those variables that are directly specified. Furthermore, as was revealed by the deliberations of the Ozone Trends Panel (1988), the best trend determination is often determined by explicitly computing the behaviour of separate observational streams. Bengtsson *et al*. (2004) and Santer *et al*. (2004) perform trend analyses with reanalysis datasets; their work will be discussed more thoroughly below.

An important product from the first and second generation reanalyses is the quality-controlled input data record (Onogi 2000; Haimberger 2006). This examination of the input data record comes from comparing the input data stream with model estimates of expected values as well as with neighbouring observations. Information is provided on both global and local observing systems. For instance, it is possible to establish jumps in mean quantities as satellite instrumentation changes as well as to quantify changes in instrument performance. For the radiosonde network measurement differences between the instruments used by different countries and provided by different vendors are quantified. For other types of observations, for example shipboard observations, it is possible to identify systematic errors that establish that the observing sensor is not at the reported altitude above the sea's surface. The quality control information obtained from reanalysis projects is a potentially rich research product that is underutilized. As institutions push forward with new reanalyses, they are committed to sharing these quality-controlled input datasets. This will improve the robustness of future conclusions drawn from reanalysis datasets as one source of non-geophysical variability will be reduced.

There are other unique lessons learned from the reanalysis activities. One is that modern assimilation systems applied to the historical observations improve forecasts. A number of notable forecast failures in the pre-satellite era have been studied and forecast quality is greatly improved (see Kistler *et al.* 2001). This validates that research investments in model development and the evolution of assimilation methodology have beneficial impact. Another result of note is that methods of data treatment that have been applied in weather prediction might have to be reconsidered in climate applications. For instance, direct consideration of aerosol radiative effects on infrared observations might be important during periods of volcanic activity to assure the accurate use of radiances. Finally, the reanalyses help to focus attention of those observations needed to address the key uncertainties in energy, moisture and constituent budgets, providing guidance for future observing systems.

Heterogeneity of the input data stream.The input observations used in reanalysis come from many sources. Historically, the bulk of the measurements to be assimilated are extracted from those collected, operationally, for weather forecasting. These measurements include observations of the surface conditions over land and ocean, observations from weather balloons and airplanes, and remotely sensed observations from satellites. The instruments used to make these observations were not designed with calibration standards to establish long-term, climate-quality datasets. Further, observing systems deployed by different countries and different agencies within countries were not (and are not) procured and deployed in a way to assure consistent accuracy.

Added to the observations collected for operations are those observations collected for research. A present and growing practice is to use research observations in operational applications (chapter *Research Satellites*, Lahoz). Reanalysis projects are ideally suited to include research-data streams that were not appropriate for real-time applications when they were originally collected. Some of these research observations were collected in campaigns of limited temporal span and spatial extent. Others have been collected during multiyear satellite missions. Data archeology, pioneered by Roy Jenne at the National Center for Atmospheric Research in the United States, recovers some of these research data so they can be brought to bear on reanalysis problems. These recovered datasets are especially important for the quality of the reanalyses prior to 1960.

One of the most obvious discontinuities in the observing system is the beginning of the record in 1979 of operational, polar-orbiting satellites. Prior to this time, the upper air observing system was dominated by order 10^5 radiosonde observations per day. The radiosonde observations were (and are) concentrated in the Northern Hemisphere. Besides differences in spatial and temporal coverage, the jump in 1979 is related to specific characteristics of the profile-by-profile observations. For example, the vertical resolution of the radiosondes is much higher than that of the satellite observations. One result of this is that near the tropical tropopause the poorer resolution of the satellite observations manifests itself as a positive temperature bias. There are numerous sources of bias between radiosonde and satellite temperature observations, and these vary with space and time.

A specific, subtle example of the impact of input data heterogeneity is from the radiosonde network itself (Lait 2002; Redder *et al.* 2004; Haimberger 2006). Radiosondes provide what some consider to be the single most important class of observations of the upper air. This might be arguable in the current era of high quality satellite observations and as satellite assimilation techniques improve, but there is no argument that the radiosonde network is of paramount importance prior to the satellite era (see chapter *The Global Observing System*, Thépaut and Andersson). The radiosonde measurements have benefited from much scrutiny, and strategies to develop climate quality datasets have been exercised. Different countries use different types of radiosondes, and within a country, several manufacturers of radiosondes are used. There is no consistent calibration of radiosondes.

Lait (2002) examines the impact of the heterogeneity of the radiosonde network on the quality of the assimilation analysis. Lait subtracts the zonal mean geopotential height from that of the radiosonde observation. This reveals persistent anomalies clustered by radiosonde type. A regional aspect of this impact is shown in Fig. 1. The left panel shows the radiosondes over eastern Europe, colour coded by manufacturer. The right panel shows the difference of the geopotential height from the zonal mean, still, colour coded by manufacturer. The eastward lying observations are between 30 and 40 geopotential metres higher than the westward lying observations. This height gradient is persistent with altitude. A wind error of order 5 ms^{-1} is consistent with this height gradient in a part of the atmosphere where the expected wind speed is order 10 ms^{-1}. Lait (2002) identifies persistent wind patterns, seemingly spurious rivers of air, surrounding regions of differing radiosonde instrumentation. Again, this is directly related to biases in the observations of fundamental geophysical parameters (see chapter *Bias Estimation*, Ménard).

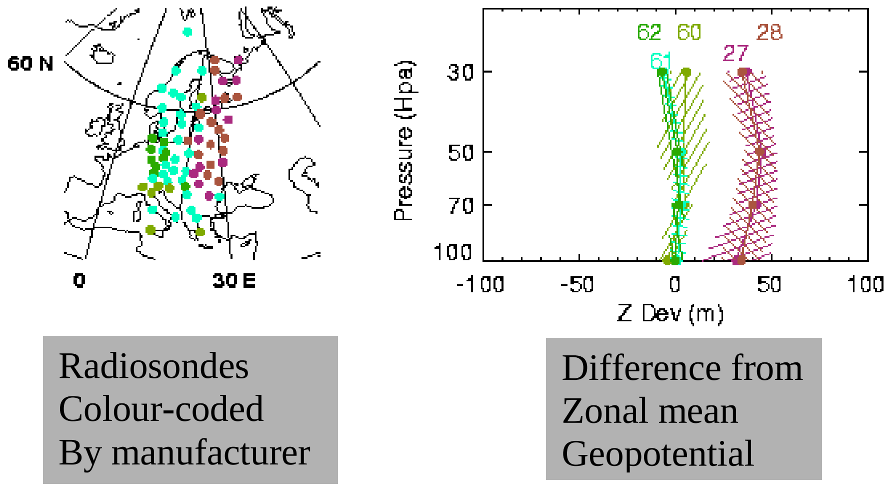

Fig. 1. From Lait (2002). The left panel shows the distribution of radiosondes observations over eastern Europe, colour-coded by manufacturer. The right panel shows the difference of the radiosonde heights from the zonal mean analysis. The different types of radiosondes group together, and a spurious circulation separates the different types of radiosondes. See also Rood (2003).

The discussion above brackets the extremes of the issues associated with data heterogeneity. At one extreme, when a new global observation type is added to the observing system, large changes in the assimilated data product are realized. In the case of the radiosondes, subtle biases between different types of radiosondes were shown to have large enough impact on the analysis of wind to impact the quantification of atmospheric transport. Between these two extremes are a whole set of impacts that might be expected when new data types are introduced. For example, the introduction of scatterometry data to define the ocean surface winds or precipitation observations to define the hydrological cycle will, no doubt, improve the quality of the assimilated data product. However, these improvements will be accompanied by changes in mean quantities such as surface pressure, precipitation, and outgoing longwave radiation; hence, leaving a signal in the reanalysis time series that is not of geophysical origin.

Alternatively, the exquisite sensitivity of the reanalysis to the input data stream suggests that the assimilation process is an outstanding monitor of the quality of the observing system. Štajner *et al*. (2004) provide one example of using assimilation to monitor the observing system by detecting variability as a function of satellite scan angle, changes in retrieval techniques, and orbital degradation.

Impact of bias. Data assimilation theory has been implemented, primarily, under the assumption that the information from the observations is unbiased relative to the information from the model (see chapters in Part A, *Theory*). That is, given a parameter such as temperature, the time mean of the observations subtracted from the mean of the model prediction is zero. However, as the previous discussion on heterogeneity in the observing system shows, the observations themselves are biased relative to each other even within the same nominal instrument type, *e.g.* the radiosondes and the succession of operational satellites. Different observing systems measuring the same geophysical parameter are expected to have bias between each other. There are systematic errors in the models. These systematic errors have regional and temporal dependencies. The assimilation quality is impacted by the bias between model prediction and observations as well as the bias between different pieces of the observing system.

One of the classic bias problems of data assimilation is known as the "spin-up" problem. Precipitation is determined to first order by the estimation of temperature and humidity and the use of these estimates by the physical parametrizations of the model. In the absence of assimilation the model determines precipitation based upon the model's temperature and humidity. Often when the observation-corrected temperature and humidity that comes from the assimilation are used, precipitation far in excess of that which is observed is estimated. This biased estimate of precipitation suggests that fundamental processes in the model are not well represented on the scale of the observations; *i.e.*, there is substantial model error. In this case, since temperature is relatively smooth and estimated well by the model, the errors can be linked to the moisture field. It is often the case that the vertical structure of the moisture field is in error. Specifically, there is a discrepancy between amount of moisture modelled and observed in the planetary boundary layer, as contrasted with the upper troposphere. Over the course of the forecast, excess moisture rains out and the model "spins up" to a balance.

From the point of view of short-term prediction, directly assimilating information that corrects the physical parametrizations can have a large positive impact. Hou *et al*. (2001, 2002) have shown that assimilating satellite precipitation observations improves both forecast skill and the estimate of important metrics of the climate system, for example, outgoing longwave radiation. Still, however, the physical processes in the model are always tending towards their biased state, and the correction by the insertion of observations is not without consequence. The general circulation, the time averaged, spatially averaged dynamics of the atmosphere, is where the consequence is usually realized (see, for example, Chen *et al.* 2008a). This will be discussed more thoroughly in the section on constituent transport modelling.

Ultimately, the quality of assimilation analyses will be dependent on eliminating the bias between the model and the observations. Assuming that the observations can be corrected in some way to eliminate the bias between different instrument types, the elimination of bias between the model and observations relies on improved model quality. Much of this improvement will come from better physical parametrizations and will require reformulation of physical parametrizations. Such development will be based on improved, more complete observations and modelling algorithms that can utilize the observed information. In the meantime, however, there is potential benefit derived from bias correction.

Figure 2 demonstrates a prescribed, idealized system and an estimate of that system by model-data assimilation. The smooth line shows the known mean state, *i.e.*, climate. The segmented line shows a series of model forecasts corrected intermittently by a set of observations that, over time, are randomly distributed around the known mean state. In the top plot the model forecast is unbiased; in the bottom plot the forecast is biased. In both plots the observations are unbiased. At a given time, 1979, the observing system is changed so that more observations are taken. This is symbolic of the increase in temporal and spatial resolution that occurred when satellite observations became operational. In the top plot when the model predictions are unbiased, the mean error in the analysis remains essentially the same before and after the change in the observing system. In the bottom plot, where the model prediction is biased, the increase in density of the observations reduced the mean error in the analysis by half, leaving a jump in the estimate of the mean state. Therefore, even if the mean state of the observations is homogenized prior to assimilation through some calibration procedure, as long as there is model error, reanalyses will be subject to errors based simply on improved data coverage.

Dee (2005) investigates the role of bias in assimilation. Dee posits that all components in the assimilation system are a potential source of bias and can propagate and enhance bias. Techniques to account for the bias require the use of ancillary information that may come from independent observations of known quality or theoretical evaluation of the source of the bias. In some cases it is not difficult or expensive to estimate bias and apply a correction algorithm (Dee and da Silva 1998). This can improve the quantitative integrity of the assimilated dataset and have positive impact, especially on prediction of parameters that are being assimilated. However, the bias correction is ultimately compensating for shortcomings in the system. This often implies that the model physics (or chemistry) are not correct, and this will ultimately manifest itself somewhere in the assimilated dataset.

Dee (2005) investigates the development of bias-aware assimilation techniques. With consideration of the possible sources of bias, it is possible to develop adaptive techniques to compensate for the bias. This is a formidable and, sometimes, imprecise task as bias is known to have multiple sources with spatial and temporal variability. As pointed out by Dee such techniques will "by construction, reduce the mean analysis increments, but not necessarily for the right reasons." The role of bias in data assimilation remains a fundamental problem (see chapter *Bias Estimation*, Ménard), and it is of particular importance to the development of reanalyses for climate and constituent transport applications.

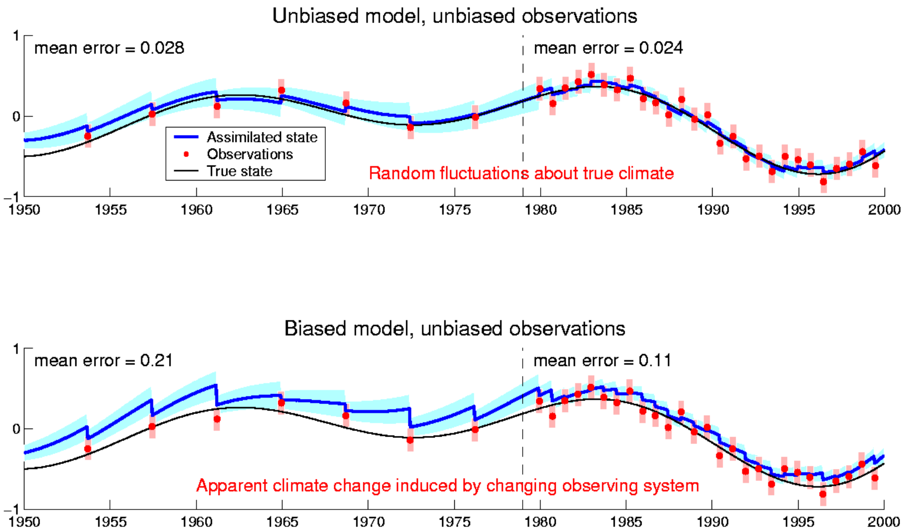

Fig. 2. This figure is adapted from Dee (2005). The solid line represents a known true state of an idealized climate system. The red dots are observations of the system. The blue lines are model forecasts of the mean state following assimilation of the observations into the model. In the top frame the model is not biased. In the bottom frame the model is biased. (Figure courtesy of D.P. Dee; see also Rood 2003)

The temporal averaging or smoothing that is intrinsic in the 4D-Var (four-dimensional variational) assimilation technique (see chapter *Variational Assimilation*, Talagrand) can reduce the effects of certain types of bias; however, there is nothing intrinsic in 4D-Var that eliminates the effect of bias through first principles. The type of bias that is most impacted is that where the model forecast is accurate and the statistics of the observations are such that a temporal average over the time interval of the forecast-assimilation cycle are unbiased relative to the model. Persistent biases that are related to the inadequacies of model representation of variables or instrumental characteristics will continue to impact negatively the assimilated data product in 4D-Var systems.

Impact of data heterogeneity and bias on trend determination. Simmons *et al.* (2004) investigate surface temperature trends in reanalyses and surface station observations and find complex relationships between the observation system and spatial and temporal scales. Bengtsson *et al*. (2004) assess the ability to determine trends with the ERA-40 reanalysis for several geophysical parameters. They investigate directly constrained variables (temperature), weakly constrained variables (integrated water vapour), and derived parameters (kinetic energy). If trends are calculated without regard to the observing system, then large spurious trends are found in all of the parameters. If the datasets are split into segments where the observing system is quasi-homogeneous then more convincing trends are determined. With special scrutiny, it is possible to provide corrections that improve the trend determination. Still, this study concludes “that there is significant uncertainty in the calculations of trends from present reanalyses data." (Bengtsson *et al.* 2004).

Bengtsson *et al*. (2004) studied, primarily, global trends. The global average has the potential for errors to compensate in the averaging process. Bromwich *et al*. (2007) compare ERA-40, NCEP/NCAR, and JRA-25, with a focus on representation of high latitudes; they also provide a good introductory summary of the attributes of the different products. They note that the reanalyses are more accurate in the Arctic than the Antarctic, introducing the idea that there is regional heterogeneity in the quality. Further, they show that the summertime is more accurate than the wintertime, especially before the availability of satellite data. Hence, there is temporal heterogeneity in reanalysis products. There are significant differences between the reanalysis products. In the case of the Polar Regions, there are significant differences in atmospheric circulation and the propagation of weather-scale waves. Bromwich *et al*. (2007), also, point out significant sensitivity to the details of the satellite observing system revealed in the preparation for NASA's Modern Era Retrospective-Analysis for Research and Applications (MERRA); it is not simply a matter of satellite/no satellite.

In the case of the MERRA reanalysis, the Special Sensor Microwave/Imager (SSM/I) is a significant change in the satellite data observing system, being a new instrument yielding profiles of moisture and temperature. Onogi *et al.* (2007) show a change in precipitation (an improvement) with the availability of SSM/I. Bosilovich *et al.* (2008a) tested the impact of SSM/I in July/August 1987, when it is initially available. Figure 3 shows that there is a change in the character of precipitation in the MERRA system. This leads to a 10% increase in tropical (15^{o}S-15^{o}N) precipitation when SSM/I radiances are assimilated.

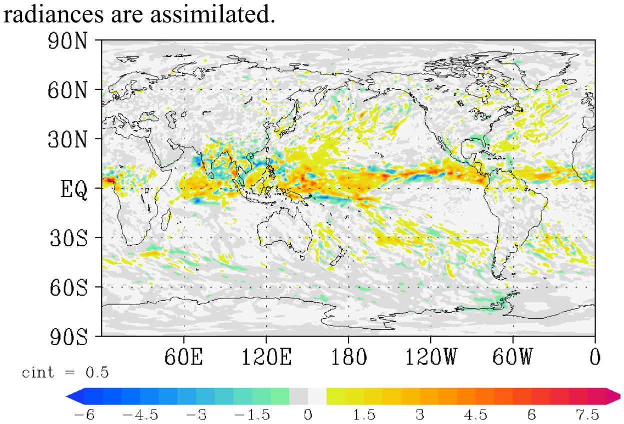

Fig. 3. Data impact test of the inclusion of Special Sensor Microwave/Imager (SSM/I) in the GEOS-5 data assimilation system to be used for MERRA. August 1987 monthly mean precipitation difference between two experiments, with and without SSM/I radiance assimilation is shown. Units are mm.day^{-1}. Red indicates positive differences (experiment with SSM/I radiance assimilation has higher values); blue indicates negative differences (experiment with SSM/I radiance assimilation has lower values).

Santer *et al.* (2004) use both first and second generation reanalysis products to investigate possible trends in tropopause height and the attribution of that trend to greenhouse gas global warming. This study provides a summary of the strengths and weaknesses of reanalysis products, and emphasizes the importance of the coherent dynamical structure provided by the reanalyses in determining trends. This coherency helps to define correlative behaviour between geophysical parameters and contributes to the definition of "fingerprints", which can be used to distinguish cause and effect mechanisms for observed trends in warming. Santer *et al.* (2004) compare the temperature provided by the reanalyses with standard observational datasets that are used in trend detection. Using this comparison to verify the performance of the reanalysis, they derive the behaviour of the tropopause height. The data assimilation provides the estimate of the tropopause height, which is correlated with the temperature observations used in the verification process. This use of external observations and careful examination of correlated physics serves as an example of a strategy for applying reanalysis datasets to trend studies.

Chen *et al.* (2008a) demonstrate the complexities of using reanalysis products in the determination and attributions of trends. They explicitly discuss the impact of data discontinuities on the quality of the reanalysis. Using the idea that the reanalyses provide a dynamically coherent estimate of spatial and temporal variability, Chen *et al.* develop a technique to remove El Niño – La Niña variability from the longer-term time series. With this method they estimate the part of the temperature change due to global warming, including regional estimates. A fascinating result from the Chen *et al.* (2008a) study is that the NCEP/NCAR reanalysis shows an atmospheric response in the Walker Circulation, and the ECMWF ERA-40 shows the atmospheric response in the Hadley Circulation. These features of the general circulation, which are related to the divergence of the wind and the dissipation of waves, are the most difficult for assimilated datasets to represent.

3 Lessons from applications

The following two applications, hydrometeorology and constituent transport modelling, will be used to demonstrate the scientific challenges that remain for reanalysis. Both of these problems are characterized by the fact that effective quantitative analysis requires the conservation of key physical variables: mass, momentum, and energy. The challenges that are faced and the deficiencies that are revealed demonstrate that in reanalysis datasets the insertion of the observations is a significant source or sink term in the conservation equation. In both applications, the conservation budgets with a non-assimilating model are more consistent, physically, than in the case of assimilated data. This fact points directly at the role of bias. To be clear, assimilated datasets are *not* consistent from a physical point of view as long as biases are being corrected by the insertion of observed information. The correction of bias through assimilation propagates and enhances biases throughout the system (see Dee 2005). The geophysical quantities from an assimilated dataset are constrained or informed by observations, perhaps they are a better match to observations than the unconstrained quantities, but the fabric that connects the variables, the correlated physics, is not the same as in the atmosphere. How well or how poorly correlated behaviour is represented is a function of both spatial and temporal scales. In particular, slow processes in the atmosphere – those features that are associated with residual circulations like the Hadley cell, the Brewer-Dobson circulation, and the

Walker circulation (see chapter *General Concepts in Meteorology and Dynamics*, Charlton-Perez *et al.*), are not likely to be well represented.

Hydrometeorology. One of the key utilities in a reanalysis is that the output generated from the model physics provides information about variables that are not easily observed, but are informed by the analysed observed information. Uncertainties are a complex mix associated with observations, models, and implementation of analysis techniques. Betts *et al*. (2006) and Bengtsson *et al.* (2007) summarize strengths, weaknesses and the utility of reanalyses, especially regarding hydroclimate studies. Trenberth and Smith (2008a, b) and Trenberth *et al*. (2008a) investigate, thoroughly, the energy budget in reanalyses. Betts (2004) provides a framework for using the correlated physics of hydrometeorological observations to analyse the underlying quality of global modelling and assimilation systems. This framework connects surface processes, radiative transfer, clouds, water, precipitation, and evaporation. While the method shows promise both in understanding the model and assimilation systems as well as the Earth's processes, challenges remain in verifying the connective processes. Betts and Bosilovich (2008) investigated the hydrometeorological connections in preliminary MERRA data compared to ERA-40. Figure 4 shows that coupling in the Amazon is quite different between the two systems. MERRA exhibits a wide dynamic range of evaporative fraction with little sensitivity to cloud fraction, while ERA-40 evaporative fraction increases steeply with cloud fraction. They caution that the coupling is also regionally dependent, and the differences between the systems indicate that users should take time to evaluate the processes in their region of interest.

Precipitation is an important validation metric for the climatology of reanalyses, being coupled into the energy and water cycles, as well as the dynamic circulation. Kalnay *et al*. (1996) classified precipitation as subject to large uncertainty. From a hydrometeorological perspective, observations are assimilated into reanalysis systems and the model parametrizations each affect the resulting estimate or forecast of precipitation. Newman *et al.* (2000) showed that there is internal consistency of precipitation, outgoing longwave radiation and upper level divergence within three different reanalyses, but the consistency between the reanalyses was very low.

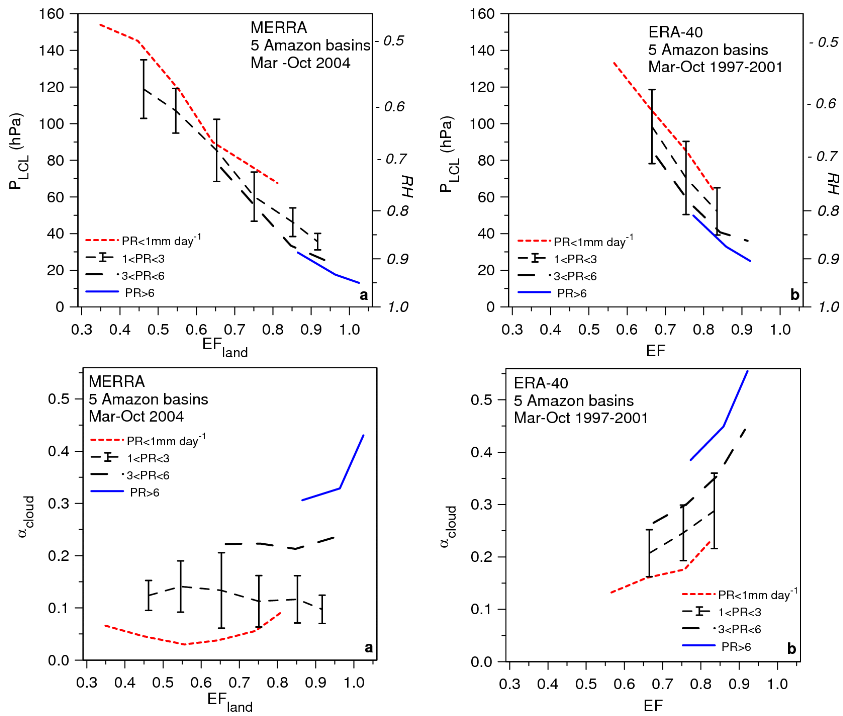

Fig. 4. Functional relationships between lifted condensation level (LCL; top plots) and cloud albedo (closely related to top of atmosphere, TOA, albedo; bottom plots) with evaporative fraction (EF) and precipitation (PR) for MERRA (a; left-hand plots) and ERA-40 (b; right-hand plots). Note that the MERRA data is a short preliminary experiment, compared to a longer time series for ERA-40.

Chen *et al*. (2008a, b) isolated the long-term trends in the NCEP/NCAR and ERA-40 reanalyses, evaluating the changes in both dynamics and thermodynamics. Figure 5 shows the long-term trend of the Hadley (top) and Walker (bottom) circulations. The Hadley circulation in ERA-40 has changed significantly in time, and this may be related to a spurious trend in latent heating by precipitation and the variations of the observing system. On the other hand, the NCEP/NCAR reanalysis shows change in the Walker circulation, correlated to changes of sea surface temperatures, which are prescribed by observations. The representation of these tropical circulations requires accurate representation of both dynamics and heating. The relationship between vertical motion and latent heating directly connects the divergence of the horizontal wind and the physical parametrizations. Both of these quantities are difficult to calculate. Precipitation is an integrated measure of this balance.

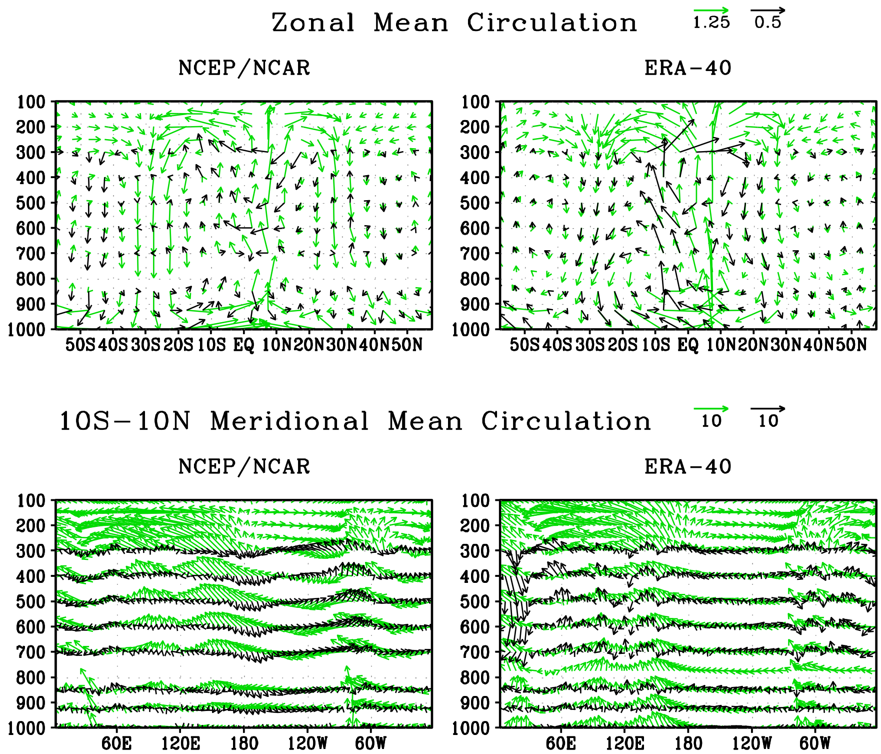

Fig. 5. The circulation changes (black vectors) associated with the global warming trend mode in the zonal mean meridional-vertical cross section (upper row) and the 10°S-10°N meridional mean zonal-vertical cross section (lower row). Left column: NCEP/NCAR reanalysis data. Right column: ERA-40 reanalysis data. The climatology is drawn in green vectors. In the upper plots, showing the Hadley circulation, the horizontal component of the vectors is meridional wind with unit 1(ms^{-1}), and the vertical component of the vectors is negative ω with unit –1/60($hPa.s^{-1}$). In the lower plots, showing the Walker circulation, the horizontal component of the vectors is zonal wind with unit 1(ms^{-1}), and the vertical component of the vectors is negative ω with unit –1/120($hPa.s^{-1}$). The arrow lengths of the vectors are scaled as shown on the top of each row. From Chen *et al.* (2008a).

Bosilovich *et al.* (2008b) used eight operational assimilation systems to investigate the uncertainties of the precipitation and outgoing longwave radiation. An ensemble average and variance were produced. Figure 6 shows the comparison of each of the analyses and ensemble average precipitation with precipitation from the Global Precipitation Climatology Project (GPCP, Adler *et al.* 2003, http://precip.gsfc.nasa.gov/). The global ensemble of analyses has lower error than any of the contributing members. Since, essentially the same observations are used in all of the analyses, the correlated features related to the observations should remain (both positive and negative). Uncorrelated model errors in the analyses can be minimized through the ensemble average. This suggests that an ensemble of reanalyses may provide some benefit. However, since this is a statistical formulation, it remains to be seen the degree to which such an ensemble may adhere to the physical principles that govern the Earth's processes.

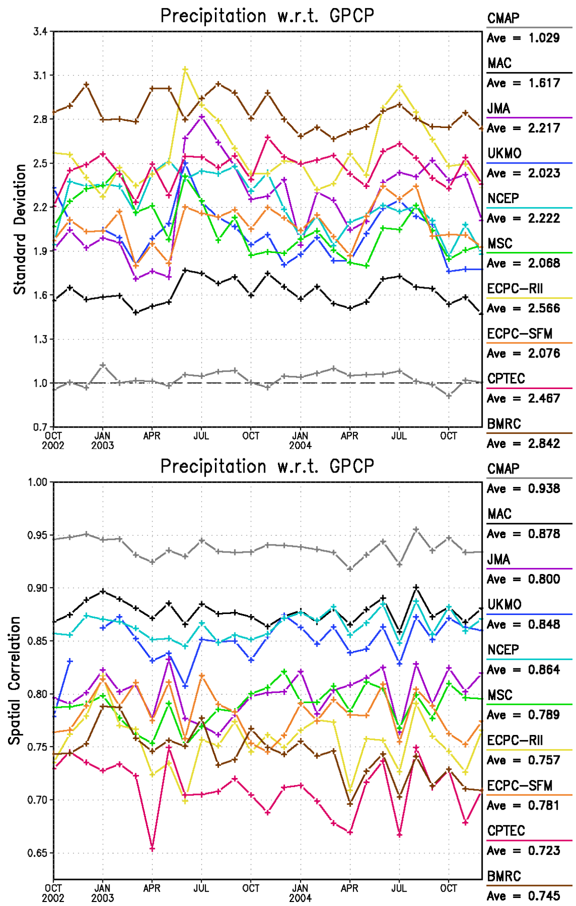

Fig. 6. Standard deviation of the monthly global differences of eight operational analyses (identified by colour – see right hand of plots) and their ensemble average (labeled MAC) from the Global Precipitation Climatology Project (GPCP, Adler *et al.*, 2003 http://precip.gsfc.nasa.gov/) (top plot) and spatial correlation to GPCP (bottom plot). The Climate Prediction Center Merged Analysis of Precipitation (CMAP, http://www.cpc.noaa.gov/products/global_precip/html/wpage.cmap.html) global precipitation observations are provided as a measure of observational uncertainty.

Terrestrial drainage is a primary source of fresh water for the Arctic Sea, and so is an important component of the climate system (see chapter *Land Surface Data Assimilation*, Houser *et al.*). Several studies have applied reanalysis precipitation as forcing for river discharge models. Serreze and Hurst (2000) found reasonable spatial patterns at large scales and high northern latitudes in reanalyses. There were some notable seasonal biases (better in winter, worse in summer). Precipitation bias was related to high incoming shortwave radiation, which provided energy for evaporation and then precipitation. Pavelsky and Smith (2006) used two reanalyses and two observed precipitation data products, showing that a few positive aspects in the reanalyses were offset by substantial errors in variability and trends of the data. At high latitudes the quality and completeness of the direct observations have significant problems; for example, blowing snow leads to an underestimate of precipitation. Serreze *et al*. (2003) conclude that, while needing improvements, reanalyses are useful to study the high latitude water cycle. Cullather *et al*. (1998) find that reanalyses generally agree on the main features of Antarctic precipitation, but focusing on any region may lead to discrepancies. Teleconnections between ENSO (El Niño-Southern Oscillation) and Antarctic precipitation are influenced by how effectively observations input to the reanalysis are used (Bromwich 2000).

Basin scale studies in well-instrumented regions allow comprehensive budget studies and the potential for independent observations to validate reanalysis systems. Hagemann and Gates (2001) used large basin scale discharge to compare reanalyses and identify weaknesses in the physics parametrizations. Fekete *et al*. (2004) also computed runoff from observed and reanalysis precipitation, and found the largest errors and sensitivity in arid and semi-arid regions. Basin scale studies allow for the evaluation of the coupling of the water and energy cycles in reanalyses (Roads and Betts 2000), but also the assessment of the impact of observations through the data assimilation and the spin-up in the subsequent forecast (Viterbo and Betts 1999). Schubert and Chang (1996) used multiple linear regression and the time series of analysis increments of atmospheric water and the atmospheric water budget to attribute the analysis increment contributions back to corrections of precipitation and evaporation. This method was later applied to monthly mean reanalysis water budgets with favourable comparisons to observations (Bosilovich and Schubert 2001).

Major issues remain in trying to improve the hydroclimate of reanalyses; these require continued research if they are to be addressed. One strategy takes advantage of the physical consistency realized in the stand-alone climate models. Then limited observing systems are used to constrain a particular attribute of the model. The model then evolves with this limited constraint. An example of this strategy is to use an ensemble of reanalyses using only surface pressure to provide 100 years of reanalyses data and include uncertainty estimates (Compo *et al*. 2006).

Constituent transport modelling. Rood *et al.* (1989) first used winds and temperatures from a meteorological assimilation to study stratospheric transport. Since that time there have been productive studies of both tropospheric and stratospheric transport. However, a number of barriers have been met in recent years, and the question arises - has a wall been reached where foundational elements of data assimilation are limiting the ability to do quantitative transport applications? Stohl *et al.* (2004; and the references therein) provide an overview of some of the limits that need to be considered in transport applications. Chapters *Constituent Assimilation* (Lahoz and Errera) and *Inverse Modelling and Combined State-source Estimation for Chemical Weather* (Elbern *et al.*) discuss the assimilation of constituents.

In transport applications, winds and temperatures are taken from a meteorological assimilation and used as input to a chemistry-transport model. The resultant distributions of trace constituents are then compared with observations. The constituent observations are telling indicators of atmospheric motions on all time-scales. Ultimately, how constituents are distributed in the atmosphere is related to the general circulation of the atmosphere. This is linked to the divergent component of the wind and/or vertical motion. The general circulation is determined by the dissipation of dynamical features. Data assimilation for weather prediction focuses on the propagation of dynamical features, and the dissipation of these features occurs on time-scales that are long compared with the forecast time-scale. In fact, dissipation often occurs outside of the model domain (*e.g.* the stratosphere), and dissipation is highly sensitive to the insertion of observations. There are fundamental, conflicting requirements of data assimilation for weather prediction and for climate diagnostics.

Constituent observations are often of very high quality and come from many observational platforms. They are markers of motion. As a community, rigorous quantitative Earth science has been significantly advanced by comparison of constituent observations and model estimates. Overall, it is found that the meteorological analyses do a very good job of representing variability associated with synoptic and planetary waves. This has been invaluable for accounting for dynamical variability, and allowing the evaluation of constituents from multiple observational platforms. On the other hand, those geophysical parameters that rely on the representation of the general circulation, for instance the lifetimes of long-lived constituents are poorly represented.

Douglass *et al.* (2003) and Schoeberl *et al.* (2003) each provide detailed studies that expose some of the foundational shortcomings of the physical consistency of data assimilation. In their studies they investigate the transport and mixing of atmospheric constituents in the upper troposphere and the lower stratosphere. Figure 7 from Douglass *et al.* (2003) shows ozone probability distribution functions in two latitude bands from four experiments using a constituent transport model. In three of these experiments, Panels B, D, and E, winds and temperatures are taken from an assimilation system. In Panel C are results from an experiment using winds from a general circulation model (GCM) simulation; that is, a free-running model without assimilation. Panel A shows ozonesonde observations; the sondes reflect similar distributions in the two latitude bands. In all of the numerical experiments, the means in the two latitude bands are displaced from each other, unlike the observations. In the three experiments using winds from different data assimilation systems (DAS), the half-width of the distributions is much too wide.

There are a number of points to be made in this figure. First, the winds from the assimilation system in Panel B and the model in Panel C both use the finite-volume dynamics of Lin (2004). Therefore, these experiments are side-by-side comparisons that show the impact of inserting data into the model. Aside from developing a bias, the assimilation system shows much more mixing. As Douglass *et al.* show, the instantaneous representation of the wind is better in the assimilation, but the transport is worse. This is attributed to the fact that there are consistent biases in the model prediction of the tropical winds and the correction added by the data insertion causes spurious mixing. Tan *et al.* (2004) also investigate the dynamical mechanisms of the mixing in the tropics and the subtropics and find systematic errors consistent with these results. Second, the assimilation systems used for Panels D and E, have a different assimilation model, and their representation of transport is worse than that from the finite-volume model. This improvement is attributed to the fact that the finite-volume model represents the physics of the atmosphere better, in particular, the representation of the vertical velocity. Third, the results in Panel B show significant improvement compared to the older assimilation systems used in Panels D and E. Older assimilation systems have had enough deficiencies that scientists have shied away from doing tropical transport studies. Thus, this example demonstrates both the improvements that have been gained in recent years and indicate that the use of winds from assimilation in transport studies might have fundamental limitations.

Figure 8 is from Schoeberl *et al.* (2003). The Schoeberl *et al.* study is similar in spirit to the Douglass *et al.* study, but uses Lagrangian trajectories instead of Eulerian advection schemes. This allows Schoeberl *et al.* to address, directly, whether or not the spurious mixing revealed in the Douglass *et al.* paper is related to the advection scheme. In this figure the results from two completely independent assimilation systems are used. The two assimilation systems are labelled UKMO (United Kingdom Meteorological Office, now, the Met Office) and DAO (Data Assimilation Office, now, the Global Modeling and Assimilation Office). The DAO system uses the finite-volume dynamical core and the panel labeled GCM (general circulation model) uses the finite-volume GCM. Vertical winds are calculated two ways. They are calculated diabatically using the heating rate information from the assimilation system and they are calculated kinematically, through continuity, using the horizontal winds from the assimilation.

The figure shows, first, the impact of the method of calculating the vertical wind using the diabatic information. When the diabatic information is used there is much less transport in the vertical. While this is, indeed, generally in better agreement with observations and theory, the diabatic winds no longer satisfy mass continuity with the horizontal winds. This result points to a self-limiting aspect of using diabatic winds in Eulerian calculations such as the ones of Douglass *et al* (2003). Second, the Schoeberl *et al.* calculations show that even with the diabatic vertical winds, there is, still, significant horizontal mixing, which is compressed along isentropic surfaces. Third, the final panel shows that for the simulation, the free-running model, there is much less dispersion, which is in better agreement with both observations and theory. Schoeberl *et al.* attribute the excess dispersion in the assimilation systems to noise that is introduced by the data insertion.

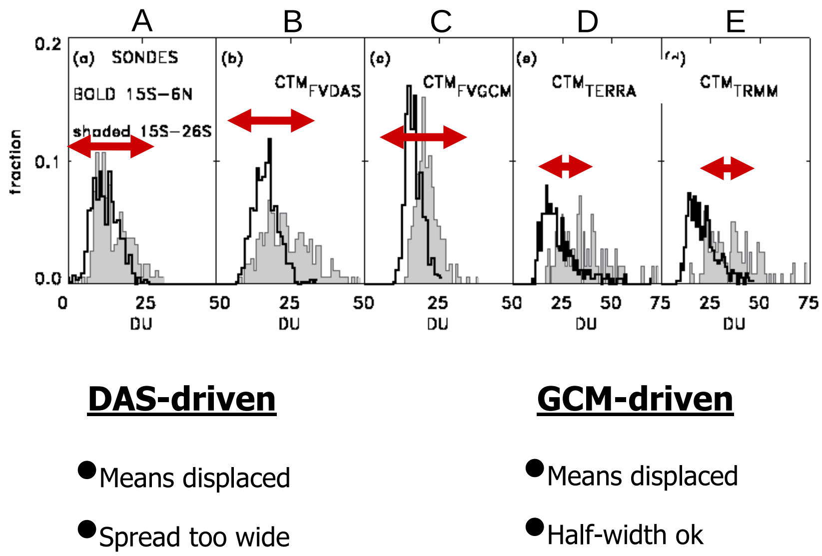

Fig. 7. From Douglass *et al.* (2003). Probability distribution functions of ozone from: Panel (A) ozonesondes; and Panels (B, C, D, E) constituent-transport models, CTM, experiments. DAS-driven is from experiments using winds from a data assimilation system. GCM-driven is from experiments using winds from a general circulation model without data assimilation.

These two studies point to the fact that the data insertion impacts the physics that maintains the balances in the conservation equations of momentum, heat, and mass. Both bias and the generation of noise have an impact. Both problems are difficult to address, with the problem of bias having fundamental issues of tractability. Again, while the data assimilation system does indeed provide better estimates of the primary variables, as the impact of data insertion is adjusted through the physics represented in the model, the derived parameters are often degraded. While there may be greater discrepancies in the absolute, day-to-day representation of constituents with free-running models, the consistent representation of the underlying physics allows more robust study of transport mechanisms and those features in the constituent data which are directly related to dynamics. The ultimate success of data assimilation for climate applications will be to preserve the physical consistency of the underlying model simulation in the presence of the insertion of observational information.

Note that recently, Pawson *et al.* (2007) have shown using NASA's Goddard Earth Observing System version 4 (GEOS-4) that the use of 6-hour averaged wind fields instead of instantaneous analyses can substantially reduce problems in stratospheric transport associated with excessive mixing and an overstrong residual circulation. Also the ERA-Interim reanalysis significantly improves the dispersion of stratospheric tracers and calculations of the age of air (*D. Dee, pers. comm.*).

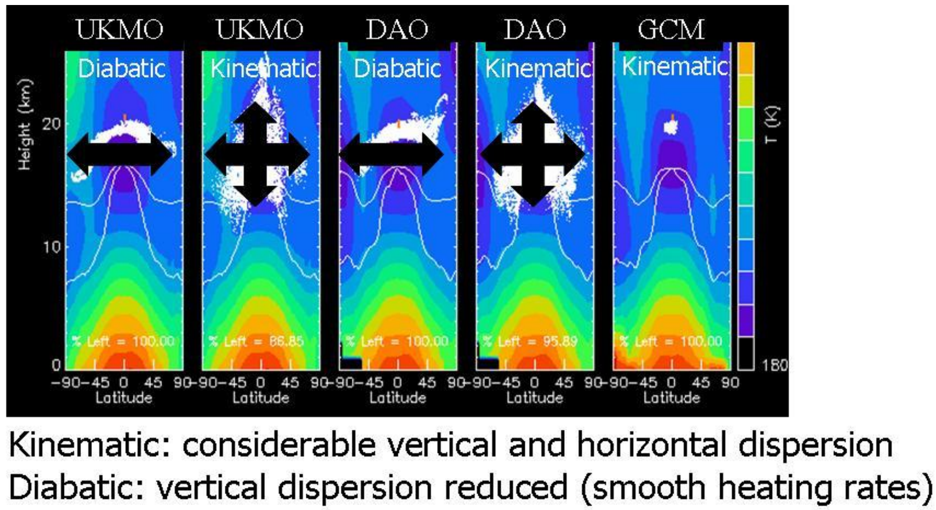

Fig. 8. From Schoeberl *et al.* (2003). The dispersion of a tracer released at the tropopause from five numerical experiments. UKMO is from the United Kingdom Meteorological Office (now, The Met Office) assimilated data. DAO is from Data Assimilation Office (now, Global Modeling and Assimilation Office) assimilated data. GCM is from the general circulation model used in the DAO assimilation. Kinematic refers to vertical velocity calculated from the divergence of the horizontal wind. Diabatic refers to vertical velocity calculated from the thermodynamic equation.

4 Summary

There is no doubt that reanalysis datasets play a central role in the modern practice of the scientific investigation of climate. Reanalyses are also used as lateral boundary conditions for regional climate models and dynamical downscaling experiments. There are thousands of references to the publications that describe the reanalysis datasets. In fact, the prominent use of "observations" that are, actually, a melding of model and observational information is a subject of interest to historians (*P.N. Edwards*, *pers. comm.*).

One reason the reanalysis datasets are widely used is that they provide an ordered and complete representation of the atmosphere that is nearly continuous in time. Reanalyses compile more observations from disparate spatial and temporal scales than individual researchers could accomplish. Furthermore, the data assimilation provides additional quality checking of those observations. Assimilation based analyses interpolate and extrapolate observational information using the physical principles of fluid dynamics to transport information. The success of the reanalysis datasets to represent atmosphere winds and temperatures in middle latitudes is remarkable. With this information it is possible to estimate dynamical variability and to bring observations scattered in space and time to a common framework. The successes are greatest for middle latitude problems and for problems with the intrinsic time scales of weather forecasting – days.

For problems of longer and shorter time-scales, for problems in the tropics and the poles, for problems that rely upon the subscale physical parametrizations in the model, a set of deficiencies is revealed in the reanalysis datasets. Many of these deficiencies are related to bias in the assimilation system. There are tractable strategies for addressing some sources of bias. For other forms of bias, it is not clear that they can be fully eliminated. For this reason it is required that scientists maintain a critical scrutiny of reanalysis datasets in applications that require the calculation of mass, momentum, and energy budgets or the identification of temporal trends. Of special note, the ability of reanalysis datasets to provide robust geophysical information will vary by region and season. The propagation of biased information through the reanalysis system means that reanalysis datasets are not geophysically consistent.

The reanalysis datasets reflect with exquisite sensitivity the heterogeneity of the observation network. The act of performing a reanalysis does not eliminate the granularity of the observing system or relegate the granularity to being small enough to ignore. In fact, the sensitivity to granularity in the observing system is another factor motivating the development of a calibrated climate observing system (see, for example, Trenberth *et al*. 2002). Of course, we do not have the luxury of building a climate observing system for the past, and climate science requires long time series of observations. Reanalysis systems have the ability to extend information from modern observing systems to the past; they can contribute to the calibration of observing systems. This requires scientific investigation to optimize the use of subsets of the observations; this is a research path that is only beginning to be followed.

Following the summary of Bromwich *et al*. (2007), Bengtsson *et al*. (2004, 2007), Santer *et al.* (2004), Trenberth *et al.* (2008b) and many others, reanalyses are a powerful tool for climate studies, which must be used with a critical eye that recognizes their limitations. The newest reanalyses, MERRA and ERA-Interim (see links at the end of the chapter), are just becoming available. They were designed to address many of the problems addressed here, and early indications are that they are an important step forward. However, it is not likely that these will eliminate all of the uncertainties in the systems. The development of reanalysis systems and techniques to address climate issues are an ongoing process, as models and data quality improve.

Acknowledgments

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Web Resources

3rd WCRP International Conference on Reanalyses, Jan 26-Feb 1, 2008: http://jra.kishou.go.jp/3rac_en.html

United States Climate Change Science Program Synthesis and Assessment Product 1.3: Re-analyses of historical climate data for key atmospheric features.

Implications for attribution of causes of observed change: http://www.climatescience.gov/Library/sap/sap1-3/default.php
NCEP/NCAR Reanalysis: http://www.cdc.noaa.gov/cdc/reanalysis/reanalysis.shtml
NCEP/DOE Reanalysis 2: http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis2.html
ERA-40: European Centre for Medium-Range Weather Forecasts: http://www.ecmwf.int/
ECMWF Interim Reanalysis: European Centre for Medium-Range Weather Forecasts: http://www.ecmwf.int/products/data/archive/descriptions/ei/index.html
http://www.ecmwf.int/publications/newsletters/pdf/115.pdf
http://www.ecmwf.int/publications/newsletters/pdf/111.pdf
JRA-25: Japan Meteorological Agency (JMA): http://www.jreap.org/
NARR: NOAA North American Regional Reanalysis: http://wwwt.emc.ncep.noaa.gov/mmb/rreanl/index.html
MERRA: NASA Modern Era Retrospective-Analysis for Research and Applications http://gmao.gsfc.nasa.gov/merra/
ASR: Arctic System Reanalysis: http://polarmet.mps.ohio-state.edu/PolarMet/ASR.html
Ocean Reanalyses: http://www.clivar.org/data/synthesis/directory.php

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