Issues Regarding the Assimilation of Cloud and Precipitation Data

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ABSTRACT

The assimilation of observations indicative of quantitative cloud and precipitation characteristics is desirable for improving weather forecasts. For many fundamental reasons, it is a more difficult problem than the assimilation of conventional or clear-sky satellite radiance data. These reasons include concerns regarding nonlinearity of the required observation operators (forward models), nonnormality and large variances of representativeness, retrieval, or observation–operator errors, validation using new measures, dynamic and thermodynamic balances, and possibly limited predictability. Some operational weather prediction systems already assimilate precipitation observations, but much more research and development remains. The apparently critical, fundamental, and peculiar nature of many issues regarding cloud and precipitation assimilation implies that their more careful examination will be required for accelerating progress.

1. Introduction

At any time, approximately 50% of the earth is covered by clouds. Through their effects on both upward and downward transmittance of radiation, they profoundly affect the surface and atmospheric heat budgets. A small percentage of the clouds are precipitating, making up a key component of the earth's hydrological cycle and, through release of latent heat of evaporation, an internal source of atmospheric heating. The accurate analysis of clouds and precipitation is therefore critical for characterizing climate. Since they directly or indirectly affect many human activities, their accurate prediction on several time scales is also strongly desired.

Remote sensing now provides critical observations for analyzing the atmosphere. The propagation of infrared or microwave radiation is strongly affected by details of clouds or precipitation, including the shape and size distributions of hydrometeors. Thus retrieving temperature and moisture fields from radiance observations in the presence of clouds and precipitation is sensitive to the characterization of these details. Since such details currently are neither analyzed nor modeled well, if at all, radiance observations suspected of being affected by them are often discarded. This includes perhaps half of all current satellite observations that could otherwise be considered for data assimilation.

The discarded satellite data presumably contain useful information, not only about the standard dynamical and moisture fields analyzed, but also specifically about the cloud or precipitation fields affecting them. Extracting the latter information is, however, not as straightforward and is more error prone than performing more standard retrievals of temperature and total water vapor in cloud-free regions. Unfortunately, in many areas of the globe, the presence of clouds, or especially precipitation, indicates that some dynamically important weather is occurring. Subsequent forecasts are also often sensitive to initial conditions in these areas. The

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correspondence of cloud and precipitation occurrence with regions of high forecast sensitivity suggests that improving initial conditions in cloudy and precipitating regions is particularly important for advancing the skill of numerical weather prediction systems.

Unlike forecasts of the dynamical fields associated with extratropical cyclones and anticyclones that typically preserve their utility beyond 6 days, quantitative precipitation forecasts beyond just 2 or 3 days have very little skill according to most common measures (Fritsch and Carbone 2004). This is undoubtedly partly a consequence of the cloud and precipitation forecasts being determined by model physical parameterization schemes that are less accurate than dynamical formulations responsible for cyclone propagation. Also, it is partly due to the forecast clouds and precipitation being more sensitive to less accurately analyzed or forecast fields, such as vertical motion. Furthermore, it is likely that clouds and precipitation are simply less predictable than midtropospheric temperature or wind components due to their smaller spatial and temporal scales (Lorenz 1969). Even quantitatively scoring such predictions is far from trivial, given their strong temporal and spatial variability.

Notwithstanding these difficulties, it is likely that the skill of quantitative cloud and precipitation forecasts can be significantly increased by reducing errors in the portions of initial condition fields that affect them. One difficult but obvious way to achieve this is to appropriately assimilate observations that are specifically affected by, and therefore indicative of, clouds and precipitation. These include data from surface rain gauges, ground-based and satellite radar or lidar reflectivity, and satellite radiances from passive infrared and microwave radiometers. Besides potentially improving forecasts, such improved analysis will provide better datasets required for validating, and thus improving, cloud and precipitation parameterization schemes. Since the output of such schemes is generally sensitive to both input and formulation errors, only with sufficiently accurate input fields can any output errors be confidently attributed to erroneous formulation.

The assimilation of cloud- and precipitation-related observations is potentially very different than that of more conventional observation types for a variety of fundamental and practical considerations. While it is possible to ignore some of the issues to be described here and still obtain some measures of success, the full potential benefits of such assimilation will not be realized until these issues are adequately investigated and resulting findings appropriately applied.

The focus of this paper is on the assimilation of observations from which cloud and precipitation information is to be inferred. Specific data assimilation techniques or observations are not discussed. Rather, the many issues that appear to be peculiar and fundamental to the specific problem of assimilating such observations are described. This includes issues concerning peculiar characteristics of the observations and models to be utilized, general predictability, choices of fields to be analyzed, statistics, and dynamics. Some of these issues have already been presented elsewhere, but in a diverse set of papers, and others have at best cursorily appeared in publications. So this is a gathering of most of them into one paper.

2. Past research

The use of satellite-derived rain rates for improving atmospheric analyses, particularly over tropical oceans, began more than 20 years ago. Empirical techniques were developed based on the inversion of simple convection schemes to retrieve moisture profiles or on diabatic normal-mode initialization to adjust the divergent circulation to satellite-derived heating rate profiles (Krishnamurti et al. 1984; Donner 1988; Puri and Miller 1990; Heckley et al. 1990; Kasahara et al. 1996; and others). Empirical approaches are still considered for some mesoscale applications (Macpherson 2001; Ducrocq et al. 2002).

After the introduction of adjoint techniques, there were several studies using variational schemes in nonoperational contexts (e.g., Zou et al. 1993; Zupanski and Mesinger 1995; Tsuyuki 1996; Zou and Kuo 1996; Kuo et al. 1997; Zhu and Navon 1999; Guo et al. 2000; Xiao et al. 2000). Many of these studies had one or more serious design flaws, including either no consideration of background error correlations or no background term altogether (so that the variational problem is ill posed), no consideration of dynamic balances, treatment of observations as near perfect, neglect of large errors of representativeness or of observation–operator (forward model) errors, misrepresentation of sizes of terms, lack of convergence of solutions, consideration of only single cases, and others. These rather fundamental flaws generally rendered the accompanying interpretations of these works and their relevance to operations questionable.

More recently, precipitation data have been assimilated in preoperational contexts where several of the earlier flaws have been corrected (e.g., Marécal and Mahfouf 2002; Treadon et al. 2003; Tsuyuki et al. 2003; Mahfouf et al. 2005; Bauer et al. 2006a,b). Most still contain a number of simplifications for computational reasons or for controlling undesirable consequences of nonlinearity. A few operational centers—including the

U.S. National Centers for Environmental Prediction, the Japan Meteorological Agency, and the European Centre for Medium-Range Weather Forecasts—already incorporate precipitation observations operationally. While still unperfected, these implementations based on optimal control theory permit explicit accounting of error statistics, clear identification of the conditions for optimality, and validation in a real, state-of-the-art forecast context.

Thus far much more effort has been devoted to the assimilation of precipitation, rather than cloud, observations because timely quantitative precipitation data from surface networks and satellite inversion algorithms have been more widely available. Even though the improvement of quantitative precipitation forecasts is a strong justification for using precipitation data in analysis systems, it seems unlikely that these additional data alone will be sufficient to reach this goal. Complementary usage of cloud observations may be necessary to dramatically increase the predictability of precipitation since the identification of cloudy regions captures rainfall precursors in a model's initial state. Cloud data, as an addition to clear-sky water vapor and precipitation observations, also provide an additional constraint on the hydrological cycle within the analysis (i.e., on the consistency between the various phases of water substance). Also, they contain information about wind divergence (in active clouds) and about rotational wind (in passive clouds acting as tracers). Clouds identify saturated regions of the atmosphere, thereby imposing a strong constraint on the temperature and humidity corrections that should be made by a given analysis system. From improved initial clouds, a more realistic description of the three-dimensional structure of the diabatic heating produced by condensation, known to interact with the dynamics, will result. This potential is greatest when the assimilation is continuous within a significant time span, as in four-dimensional variational techniques, since temporal changes in the observed cloud field can be very informative. Moreover, when assimilating satellite radiances directly, the presence of clouds is perhaps as important as that of precipitation since more area of the globe is cloud covered than precipitating. Since many requirements for both are similar or identical, it is inappropriate to effectively ignore the cloud problem.

3. Issues concerning observations

a. Choice of observable

The only source of near-global observations of clouds and precipitation currently is and will continue to be remote sensing of radiances and reflectivities. Currently, the most direct remotely sensed observations of clouds or precipitation are cloud or rain profiles from radars operating at 5–35 GHz, cloud-top temperatures retrieved from infrared radiometry, and cirrus cloud cover from lidar observations. Additionally, microwave radiances are related to path-integrated quantities such as total column rain or cloud amount, but also to temperature and moisture profiles and even to surface wind speed as it affects surface emissivity. The more diverse and complex the sensitivity of observations to meteorological parameters, the less well constrained the inversion problem is.

Satellite observations regarding clouds or precipitation can be assimilated as either raw radiances or as retrieved parameters (e.g., surface rainfall rate, cloud liquid water path, cloud optical depth, cloud effective radius, etc.). Even though the assimilation of radiances seems the most natural way for including satellite data in atmospheric data assimilation, this is by no means certain. Indeed, when the assimilation of clear-sky satellite data for numerical weather prediction began almost 20 years ago, observations were retrievals of geopotential thicknesses and integrated water vapor representative of deep layers. These retrievals were provided by space agencies to operational weather forecasting centers. At the beginning of the 1990s, column retrievals using variational (1DVAR) techniques were developed using a priori information provided by short-term weather forecasts. The retrievals were then assimilated as pseudo-observations of temperature and humidity in the full three-dimensional atmospheric analysis systems (Eyre et al. 1993; Gérard and Saunders 1999). More recently, improvements in model accuracy and data assimilation techniques have allowed the direct assimilation of raw radiances in weather prediction models (McNally et al. 1999; Bauer et al. 2003). These successive approaches have been steps in progress.

A clear disadvantage of the assimilation of derived parameters is that the a priori information from training datasets that are used for constraining the retrievals is rarely representative of the wide range of environments encountered in operational systems. Parameters such as hydrometeor content, rain rates, particle phase, or bulk particle size spectra variables require a priori information and model assumptions that are not available from the observations alone. Also, as explained in the next section, the error characterization of retrievals can be problematic.

If cloud or precipitation properties are chosen as observables, there is often no sensitivity (i.e., the Jacobian of the observation operator is zero) where the observable is zero. A significant advantage of directly assimilating microwave radiance observations is that the signals are sensitive to changes in the atmospheric state regardless of the presence of clouds and precipitation. These data can therefore produce positive moisture increments in clear sky conditions that lead to the generation of clouds and precipitation where the model background had none. This more regular behavior of the observation operator is a highly desirable feature in data assimilation (Moreau et al. 2004; also see section 4). However, the less clear distinction between processes for microwave radiances could lead to misinterpretations of the signal. Therefore, retrievals are still used in quality control for the identification of cloudy and rainy pixels (Bauer et al. 2006a).

Some observations are of time-integrated or averaged values. Examples include hourly precipitation accumulated in rain gauges or temporally continuous datasets constructed from periodic satellite observations. The use of such values tends to reduce both data volumes and random errors (the latter by implication of the central limit theorem in statistics). Of course, potentially useful information about changes in the observed field over the averaging interval is thereby absent. Such changes can be particularly beneficial in four-dimensional variational data assimilation contexts, but only if the assimilation model is able to digest such intermittent information. So, deciding what time scales of data are most useful requires consideration of several aspects of the observations and data assimilation system.

Finally, the choice of observable regarding clouds and precipitation from satellites appears to be strongly connected to the type of data assimilation system and to the ability of the model to simulate the observable (through its moist physical parameterization schemes and the model resolution). This choice is also influenced by other considerations such as error characteristics, quality control, data selection, choice of control variable, and, as importantly, computational efficiency.

b. *Observation error statistics*

There are three types of observation-associated errors that must be considered when using statistically based assimilation techniques (Eyre 1989; Ide et al. 1997). One is the error in the quantitative output signal from the observing instrument; for example, the error in an observed radiance. The other two types concern errors in relating the observation to the quantities to be analyzed, for example, radiance to grid values of moisture content. One of these, termed observation-operator or forward-model error, concerns physical parameterization schemes of various kinds and is discussed in the next section. The other specifically concerns the ability to represent observations of the real atmosphere by functions of the finite resolution fields to be determined. For example, comparison of gridded fields with an observation at an arbitrary point location generally requires interpolation. Or, a satellite footprint over which a mean radiance has been observed may not coincide with the domain of a grid box. Generally, these comparisons are imperfect, creating an unknown error of representativeness that, for some observation types, may be greater than the instrument error (e.g., during a rawindsonde ascent, point measurements of temperatures may be more accurate than the formula for interpolating temperatures between grid points).

In data assimilation, the term "bias" is often defined rather vaguely. Rather than a strict temporal or spatial mean value, it may be a value that changes, albeit slowly (Dee and da Silva 1998; Dee 2005). For some types of observations, biases can be the largest components of the errors (Deblonde et al. 2007). These biases are generally detected by comparing one set of observations with another or with estimates produced from prior (background) information. Such comparisons do not by themselves reveal which of the compared datasets actually contain the most biased error. Some assumptions are therefore required since different origins of the biases require entirely different means of removal (Dee 2005).

Significant observation and modeling biases must be removed and observation error characteristics estimated and reasonably modeled. This can be facilitated by a sensible screening procedure that only accepts data in situations for which biases are negligible and error statistics are easier to describe. Errors in such acceptable observations are then considered to be unbiased, random, and uncorrelated with errors in prior (background) information. Usually, the observation errors are also considered to be normally distributed and to be uncorrelated with either each other or with errors of other kinds of observations. It is therefore desirable to actually consider observations in a form that approximately satisfies these properties.

If the distributions of random errors are normal (i.e., Gaussian), then knowledge of their means and covariances provides a complete description of their probability distributions. If they are not normal, then other moments of the distributions become relevant, the probabilities associated with selected ranges of standard deviations can be different than those for a Gaussian, and some useful theorems regarding combining (particularly multiplying) distributions do not necessarily apply. If the distributions are approximately normal, such distinctions can often be ignored unless higher-order moments or tails of the distributions are particularly germane to the problem. While in data assimilation algorithms errors that fall within the tails of probability distributions are usually addressed by a quality control procedure, nonnormality remains a generally critical consideration when distributions are strongly asymmetric or multimodal. If these are mistreated as normal, a data assimilation can produce highly inaccurate or even unphysical results (Tarantola 1987).

If estimated (i.e., retrieved) values of precipitation rates or cloud quantities are treated as observations, the errors may be far from normally distributed. When the standard deviation of a precipitation rate error is large relative to the observed value, then the distribution must be nonnormal since the error cannot be less than -100%. If a radiance or reflectivity measurement having a normally distributed error is used to estimate a precipitation or cloud quantity related to it by a highly nonlinear function, then the estimate's error distribution is again likely nonnormal. This is the case, for example, with radar-estimated rain rates that are related to reflectivities using power laws. Also, for normal distributions, the probability of any specific point value occurring is zero, but this is not true for some errors related to precipitation or clouds. For example, a retrieval may erroneously indicate that precipitation is occurring when it actually is not, or vice versa. If either possibility is not negligible, the probability distribution of the error has a point value with finite probability. Impacts of such nonnormality on data assimilation results are described by Errico et al. (2000) although the presentation there remains incomplete.

Many nonnormal error distributions can be transformed into normal ones by a change of variable. For example, a random variable with a lognormal distribution yields a normally distributed logarithm of the variable. While such transformation may be desirable, it has two possible disadvantages. One is that it can introduce undesirable nonlinearity, as described in the next section. It can also change the interpretation of measures of the random errors; for example, one standard deviation of a normally distributed logarithm of a random variable implies an asymmetric range of values of the variable itself (e.g., see Errico et al. 2000).

Errors in observed radiances or reflectivities are expected to be more normal, uncorrelated, and random than are retrievals. This has been shown by Bauer et al. (2006a) for Special Sensor Microwave Imager (SSM/I) microwave brightness temperatures and by Chevallier et al. (2004) for Meteosat and Atmospheric Infrared Sounder (AIRS) infrared radiances. When considering high spectral resolution instruments (e.g., AIRS has 2387 channels) it is possible to select channels affected by clouds or precipitation for which the linearity assumption of the observation operator is valid (Chevallier et al. 2004; Dahoui et al. 2005) and the errors thus more normally distributed.

Retrievals generally depend on prior information and forward models. Retrieval errors therefore become undesirably correlated with each other or with those of the background. Correlations with the latter are particularly undesirable because most data assimilation formulations explicitly assume that correlations between errors of observations (in this case, retrievals) and background information are negligible (Joiner and Dee 2000). Current cloud and precipitation retrieval algorithms use independent a priori information that is obtained from limited matching of satellite observations and ground truth or from only a few regional model simulation experiments. The limitations of representativeness and potential errors embedded in the retrieval process can still therefore create undesirable correlations between errors in retrieved values.

Most operationally available cloud and rain retrieval algorithms are based on offline simulations of combined models of cloud properties and radiative transfer that are fed into a training database. Similar or refined schemes are used for the observation operators in the assimilation of radiance or reflectivity data. This means that similar errors are contained in both types of derived databases. The number of cases included in these training data bases is often limited to special observing periods or sites, yielding potentially unrepresentative algorithms for global application. This can be a significant source of error, especially biases. If errors are calculated assuming that the probability distributions of the database reflect the true distributions, error estimates of surface rain retrievals range from more than 100% at low rain rates to about 50% at moderate rates and even larger errors at high rain rates (L'Ecuyer and Stephens 2002; Bauer et al. 2002). Thus they are obviously nonnormal.

4. Issues concerning models

Data assimilation requires the use of many models, including a forecast model to propagate atmospheric states from one time to the next for temporal interpolation and extrapolation of information (e.g., in four-dimensional variational and general sequential estimation, respectively). It also requires what are called forward or observation operators that relate the atmospheric fields to be analyzed to what is actually observed. When precipitation and clouds are concerned, this necessarily includes schemes identical or related to moist physical parameterization schemes that relate specific humidity and dynamic fields to hydrometeor development. Additionally, other models may be necessary, including radiative transfer models relating cloud and precipitation fields to observed radiances or reflectivities.

a. Forward operator errors

It is difficult to validate model cloud and precipitation schemes by simply comparing their output with observations since, without extremely accurate input fields, it is impossible to distinguish the contribution to output error due to model input error from that due to model formulation error itself. Here, it is the latter that is strictly referred to as model error. Errors in the formulation of retrievals can also be termed model error.

There are many potential sources of large errors in cloud and precipitation parameterization schemes. For modeling stratiform precipitation, the largest errors are produced by simplified representations of subgrid-scale variability of supersaturation. Other sources are the modeling of ice production (sublimation and heterogeneous processes) and the coupling with convection. For convective precipitation, error sources are the simple closure assumptions that link convective properties with grid-scale variables and specifications of entrainment and detrainment rates. Errors may be inevitable, however, if subgrid-scale randomness yields a relatively large random impact on grid-mean quantities.

Radiative transfer models are very accurate if the input parameters are known. Computationally efficient and precise models are available and have already been used in data assimilation (Bauer et al. 2006c). The errors that are purely due to approximations to the solution of the radiative transfer equation are of the order of 1 K (brightness temperature) at microwave frequencies below 200 GHz (Smith et al. 2002; Greenwald et al. 2002; Bauer et al. 2006c). When model clouds are used as input, the largest sources of errors are the assumptions regarding subgrid-scale cloud variability and precipitating particle size distributions. Uncertain or inhomogeneous cloud particle size distributions or fractional cloud cover distributions varying within the line of sight are major error sources at infrared wavelengths and at microwave channels used by cloud radars.

One way to characterize model error is to compare various models that are considered equally valid. Differences in output obtained using identical input must be due to differences in model formulation. If the output of each can equally be considered as proxies for truth, then the output differences are indicative of model uncertainty or error. These kinds of differences are often examined when parameterization schemes are modified or replaced in a model. Such studies, however, do not typically attempt to interpret the resulting output differences as error estimates. Of course, if a demonstrably better scheme replaces a much poorer scheme, the differences should not be interpreted as revealing the error characteristics of the better one. Also, two schemes can be more like each other than either is to the real physics, such that statistics of differences between the two can be very uncharacteristic of either's errors. Without knowing the qualities of two compared schemes a priori, interpretations of differences as errors must therefore be made judiciously.

There have been a few attempts to estimate observation-operator error in data assimilation. By comparing 6-h accumulated precipitation forecasts using identical initial conditions and models except for convective parameterization schemes, Errico et al. (2001b) estimated that errors attributable to the schemes are approximately lognormal, with standard deviations unexpectedly corresponding to factors of 3 or greater. Bauer et al. (2006a) applied the observational method introduced by Hollingsworth and Lönnberg (1986) to estimate observation plus modeling errors for microwave radiances. This method retrieves observation errors from the spatial covariance statistics of departures between observed and model predicted values by assuming that the instrument and observation-operator errors are both spatially uncorrelated and that the observations are spatially dense. The results suggest that the standard deviations of operator errors in cloudy regions are 1.5–3 times larger than in clear-sky regions.

In a variational framework, the error variances of the observation operators combine with those of the corresponding instrument and representativeness errors to yield the total effective observation error variance. With the great uncertainties due to all three components, the total can be very large indeed. Perhaps using such realistically large values will preclude a true statistically based data assimilation system from effectively using these observations at all.

b. Nonlinearity

Most data assimilation algorithms combine information implicitly assumed to have normally distributed errors and to be related by linear, or weakly nonlinear, models. If strongly nonlinear observation operators are used instead, errors in the final analysis can be significantly nonnormal. Consequently, an analysis that is nonlinearly produced is no longer necessarily an estimate that minimizes an expected error variance, although it may be a maximum likelihood estimate (Tarantola 1987). Thus the interpretation of the analysis can be altered by nonlinearity.

Even simple nonlinearity can create multimodal analysis error distributions or corresponding cost functions (Errico et al. 2000). Several possible analyses can thus be produced when a data assimilation algorithm attempts to minimize such a cost function. Which local minimum is found will generally depend on where the iterative solution begins. The attractor basin of each such minimum can be topographically complex: starting near a particular minimum does not mean that it will be the one approached by the procedure (Curry et al. 1983). Alternatively, a scheme such as simulated annealing that determines a global minimum of the cost function can be used, but it is necessarily computationally expensive, requiring very many iterations to adequately explore the global structure of the cost function.

Most operational variational schemes use linear solvers such as preconditioned conjugate gradient techniques because of their efficiency. In what is termed the "inner loop," only tangent-linear and corresponding adjoint versions of any model operators are explicitly employed. Nonlinearity is considered by using an "outer loop" to iteratively update the reference state about which successive linearizations are performed (Tarantola 1987; Courtier et al. 1994). For computational efficiency or to affect linearization in some applications, slightly different models or different resolutions are employed within each kind of loop. As more highly nonlinear forward-observation operators are used, these distinctions may become less efficient or at least may require many more nonlinear iteration steps (Marécal and Mahfouf 2003).

The effects of nonlinearity can be difficult to characterize since they depend not only on structures of errors but also on amplitudes. In data assimilation applications, the appropriate amplitudes to consider are either those of analysis increments or the changes to the atmospheric state vector introduced during each iteration. Similarly, the shapes of errors to consider are those of either the increments or minimization descent directions (Errico et al. 1993). These nonlinearities should be carefully investigated for individual as well as combinations of processes if their effects are to be understood.

Some undesirable effects of nonlinearity can worsen when a four-dimensional variational assimilation time window is increased since important errors then have more time to grow through dynamical and physically instabilities. Without appropriate mitigation, cost functions can become highly multimodal (Andersson et al. 2005). However, using longer assimilation windows has advantages, including an ability to consider more observations, to increase effects of dynamical constraints, and to minimize the influence of background states that have poorly known error statistics. Variational formulations using a model as a weak constraint may not only be a much better application of an imperfect model (Zupanski 1997) but also yield more useful cost functions. These issues are currently being investigated in highly realistic contexts for possible operational application by Andersson et al. (2005).

c. *Additional forward-model issues*

Linearized (tangent linear and adjoint) versions of the observation operators are necessary to efficiently solve the variational data assimilation problem. Formally, these operators are defined for infinitesimal perturbations; that is, they use first derivatives. Although a linearized operator may compute and apply those derivatives correctly, in almost all applications including data assimilation the concern is with finite size perturbations. If either higher-order terms in a Taylor expansion are nonnegligible or the linearized model has a fatal property (such as a numerical instability not present in the parent nonlinear model), the minimization procedure may be too inefficient or even flounder. Thus, for any particular application, it is critical to demonstrate that not only are the tangent-linear and adjoint calculations accurate, but that they are also useful (Errico et al. 1993; Errico and Raeder 1999; Mahfouf 1999; Janisková et al. 1999, 2002; Janisková 2004; Fillion and Belair 2004; Lopez and Moreau 2005; Bauer et al. 2006a).

Parameterization schemes describing cloud and precipitation generation are not only nonlinear but also often discontinuous, with conditionals based on the state of their input. The discontinuities may be of any order, including order zero. The most obvious conditional is that determining whether or not a particular water phase or precipitation is present. A formal adjoint will be determined for the branch prescribed by the input reference state and will contain no higher order information about the possibility of condition transitions. Thus, a formal adjoint model can yield a poor estimate of the true behavior of small but finite-sized perturbation. The adjoint can be modified to account for the effect of changing the timing of a transition from one branch of a discontinuity to another (Xu 1996), but this technique has had very limited application to date and cannot account for all transitions.

To increase the utility of adjoints in variational data assimilation, simplified and more linear moist physical parameterization schemes have recently been developed. Lopez and Moreau (2005) developed a mass-flux convection scheme following Tiedtke (1989) but with several discontinuities removed. The modified nonlinear scheme compares well with the original in terms of surface precipitation, but the Jacobians of the revised scheme are much smoother, increasing significantly the range of validity of the tangent-linear approximation. Tompkins and Janisková (2004) developed a diagnostic cloud scheme as a simplified version of the prognostic cloud scheme of Tiedtke (1993). This scheme allows a realistic conversion of condensed water into precipitation, and accounts for subgrid variability of humidity within a grid box to diagnose cloud cover and cloud condensate. This formulating of a cloud scheme as more continuous is known as "regularization" (Janisková et al. 2002). Indeed, for parameterization schemes that are intended to describe effects on resolved scales by processes operating at unresolved scales (an inherently statistical problem), it does not make mathematical sense to have particular low order discontinuities since the statistical uncertainty necessarily associated with unknown details of the unresolved circulations should result in a smoothing of any ultrasharp functions. So, a regularization based on a more careful consideration of the fundamentally statistical nature of physical parameterizations is very appropriate regardless of adjoint considerations.

Physical parameterization schemes should allow assimilation of observables that are realistically described. In particular, only observations having scales comparable to the ones explicitly modeled by the schemes should be considered. Schemes that parameterize moist convection describe the effect of a population of unresolved clouds on the explicit scales of the numerical model. Generally, there is a closure problem where subgrid-scale fluxes have to be expressed as a function of resolved variables (Emanuel 1994). It is this uncertain closure that critically relates the precipitation output by the scheme to the analysis fields input to the scheme.

Different reasonable closure schemes can also produce entirely different Jacobians that relate perturbations of the output to perturbations of input (Fillion and Mahfouf 2000). Such differences therefore tend to create entirely different adjustments of the analyzed state to optimally fit observations. Examination of Jacobians of forward models is therefore critical (Fillion and Mahfouf 2000, 2003; Marécal and Mahfouf 2003; Lopez 2003).

In high-resolution models, closure schemes can be avoided by employing a more explicit microphysical formulation of hydrometeor development. The calculation of radiative transfer through clouds and precipitation also requires a more complete microphysical description than offered in present low-resolution parameterization schemes. Unless the microphysical processes are intentionally modeled to accurately describe and be validated by radiative transfer as well as hydrometeor development, they may not be useful for the former (Wiedner et al. 2004). Also, additional microphysical properties may be important for the former, including, for example, the sixth moment of the drop size distribution that particularly affects radar reflectivities (Laroche et al. 2005).

Increasing the complexity of cloud and precipitation schemes to reduce the need for discontinuities or to explicitly predict more detailed particle properties may create more difficulties than it solves. Parameterization schemes are generally designed to actually model the effects of subgrid processes on the resolved grid scales, rather than those processes themselves. In the case of convection, they model the slow stabilizing response of the resolved scales to the unresolved rapid instabilities operating on the smaller scales. While a tangent-linear version of an explicitly resolved physical instability will commonly yield growing solutions that are not halted by nonlinear stabilization processes and that therefore eventually become large enough to invalidate the linearization, the same is not necessarily true for parameterized stabilization processes. The linearization of convective stabilization may instead damp perturbations, thereby acting to maintain the accuracy of its linearization for longer periods. Without actual examination of these possibilities, it is unknowable whether the beneficial or deleterious effects of rendering a particular scheme more continuous and explicit will dominate.

5. The role of diagnostic studies

a. *General predictability*

To usefully forecast an aspect of the weather, it must be predictable. Obviously, both the forecast model formulation and its initial conditions must be sufficiently accurate. Given some inevitable level of inaccuracies in both, however, equally important is that sensitivities of the output be sufficiently small with respect to uncertainties in input and formulation. How "small" depends on the acceptable accuracy of the output and on how all the sensitivities and uncertainties combine. Estimating what is reasonably predictable provides a sound scientifically based foundation on which to build weather prediction systems (Thompson 1957). It also provides insights into the sources of any limits on prediction and thus on what mitigation is required to render further progress (Errico et al. 2002).

Most atmospheric predictability studies simply compare pairs of forecasts begun from slightly different initial conditions applied to identical forecast models. Although most focus on measures of standard midtropospheric fields (e.g., 500-hPa geopotential), some have looked at derived fields, such as vorticity or vertical velocity (e.g., Stamus et al. 1992) or at precipitation (e.g., Mullen and Buizza 2002; de Ela and Laprise 2003). None of these studies should be considered definitive, particularly regarding precipitation.

Model error obviously imposes an additional limit on atmospheric predictability. If twin experiments are performed only by perturbing initial conditions, statistics of the difference obtained from them may be compared with corresponding statistics of forecast errors to estimate the effects of model error as a residual (Tribbia and Baumhefner 1988). The interpretation of the residual as an effect of model error is valid only if the initial condition perturbations are representative of real initial errors. The initial perturbation in predictability experiments must particularly have whatever characteristics real initial condition errors have that are responsible for determining the effects of those errors on forecasts. So, if real initial condition errors are dominated by particular spatial scales and are approximately geostrophic, then the simulated errors should be designed to have these same properties. Not doing so can yield gross misinterpretations of results (Errico and Baumhefner 1987).

Predictability experiments can also be performed using either an ensemble of models or stochastic forcing representative of model error (Buizza et al. 1999; Shutts 2004). One problem with each of these approaches is that, until the statistical characteristics of a model's errors are known, it is difficult to either simulate or validate them. The largest errors, for example, due to diabatic heating produced by condensation processes, are likely state-dependent and temporally correlated. Until real errors are appropriately characterized, rather naive experiments may still have value, but vigilant care must be taken in interpreting them. As with using unrealistic initial condition errors, results can be misleading if critical characteristics of the real model errors are absent.

Many aspects of predictability, however, have yet to be learned. How do initial errors in small scales affect much larger scales, and vice versa (Tribbia and Baumhefner 2004)? What is the predictability of various measures of clouds and precipitation (time means for various forecast periods, or threshold measures)? What most limits the predictability of clouds and precipitation and how, if possible, can those limits best be mitigated? Studies exploring such questions are important in order to know what cloud and precipitation data are relevant for assimilation and what model variables can be initialized with such observations.

b. Adjoint sensitivity studies

Another way to examine predictability is to use an adjoint model to directly estimate sensitivities. These may be actual fields of the gradient of some scalar measure of model output with respect to the input fields (Errico 1997) or singular vectors (SVs) of perturbation fields that are ordered sequences of structures that grow successively slower during a period of time according to end-time and beginning-time quadratic metrics. The leading SVs are therefore those that grow the most (Farrell 1990; Buizza and Palmer 1995). When the metrics and measures are appropriate, both sensitivity and SV values and patterns can be interpreted as revealing optimal perturbations for various problems (Rabier et al. 1996; Palmer et al. 1998) and for characterizing predictability (Farrell 1990; Errico et al. 2001a).

An adjoint model can also be augmented to include an adjoint of the assimilation system to yield sensitivities with respect to observations (Baker and Daley 2000). These sensitivities are determined not only by the sensitivities to initial conditions but also by the ways the observations are actually used according to assumed error covariances (Baker 2000). This augmented adjoint has led to new measures of the impacts of observations on forecasts (Langland and Baker 2004; Cardinali et al. 2004; Errico 2007).

Adjoint-based estimates of predictability can be limited owing to their specific linear analysis. Since they are based on tangents to nonlinearly evolving model trajectories, however, for initial perturbations having the characteristics of analysis errors these estimates can be very accurate for short but significant periods, especially if only dynamics is relevant (Errico et al. 1993; Reynolds and Rosmond 2003). For tropospheric forecasts much longer than 2 days, they generally should be expected to be poor estimates of corresponding behaviors in a nonlinear context, and even for much shorter forecasts if moist processes are important (Errico and Raeder 1999). Also, just because an adjoint-derived perturbation is optimal according to some norm, it is not necessarily characteristic of real analysis errors (Isaksen et al. 2005).

Adjoint sensitivity studies are also insightful for determining which fields may require better analysis for forecasting particular forecast fields. Errico et al. (2003) and Mahfouf and Bilodeau (2007) show that accurately analyzing both temperature and moisture fields is critical for forecasting precipitation. Also, Errico et al. (2003) and Lopez (2003) show that, in precipitating extratropical cyclones, even 6–24-h wind field forecasts may be significantly improved by better analyzing low-level humidity. While initial cloud and precipitation condensate errors have negligible impact on 6-h forecast wind errors, forecasts of cloud condensate depend equally on analyzed temperature, specific humidity, and cloud water (Lopez 2003). For forecasts shorter than 3 h, these conclusions can change, depending on the choice of closure schemes for the convective parameterization. Otherwise, these conclusions so far appear robust with respect to choices of model and synoptic case. For forecasting clouds or precipitation, not adjusting the temperature as well as moisture or wind fields to better fit cloud or precipitation observations (as in, e.g., Krishnamurti et al. 1984; Kasahara et al. 1996; Marécal and Mahfouf 2000) is therefore clearly suboptimal.

6. Other considerations

a. Dynamical balance

Data assimilation systems are designed to correct the largest errors in the forecast background fields. In the extratropics, these errors generally have large vertical and horizontal scales and are approximately geostrophic (Hollingsworth and Lönnberg 1986). Thus, all successful data assimilation systems have been designed to create analysis increments having those characteristics. Besides tending to correct errors, such increments also are better retained after the model's geostrophic adjustment process. Additionally, through geostrophy, observations of either temperature or wind alone tend to partially correct errors in the other field.

Cloudy and precipitating systems are generally associated with significant ageostrophic vertical motions that are not necessarily explicitly resolved by a forecast model. They are also strongly affected by fields having small horizontal or vertical scales. The latent heating associated with condensation processes will tend to directly force ageostrophic motions at some vertical scales (Errico 1989). Although the specific scale and balance assumptions employed in present assimilation systems appear to be generally appropriate for observations in clear skies, they therefore may be insufficiently optimal for the assimilation of observations in cloudy and rainy areas. If the background error covariances employed by the assimilation system have not been carefully defined for the particular inclusion of observations in cloudy regions, redesign and retuning of the balance constraints (e.g., background covariances) may be required. Pagé et al. (2007) have recently shown that the nonlinear balance omega equation with a diabatic forcing derived from a moist parameterization scheme can be appropriate to model balanced, multivariate background error covariances.

b. Flow and geographical dependence

Until now, most operational data assimilation systems have primarily used flow-independent error statistics. Indeed, it has been very difficult to demonstrate significant skill improvements by incorporating flow-dependent variances produced using ensembles or measures of baroclinicity (Buehner 2005). This does not imply that incorporating flow dependence will not lead to very large future improvements nor that even simple approaches will not be adequate for that purpose. Indeed, the fact that short-term forecast errors grow much faster in some flow-dependent locations than others suggests that flow-dependent background error statistics should describe the errors much better than static (time independent) ones can (Beck and Ehrendorfer 2005).

Since moist parameterization schemes are generally highly approximate, model errors should tend to be larger in regions where clouds and precipitation occur. Also, the presence of clouds prevents the usage of some observations, even those associated with the same feature 6 h earlier. For these reasons, background errors may tend to be especially large in cloudy regions, yet flow-independent statistics exclude this peculiarity. So, although flow-independent statistics have proven adequate for past requirements, it is possible that the real benefits of cloud and precipitation assimilation will require better consideration of flow dependence.

c. Analysis and forecast system validations

Data assimilation systems are presently validated using many metrics. The statistics (principally means and variances) of observations minus corresponding estimates of both background and analysis values are examined. Primary are measures of forecast skill. For the latter, the most common metrics are 500-hPa height anomaly correlation coefficients and root-mean-square forecast errors of wind, temperature, or height fields evaluated for particular regions and pressure surfaces. At least one forecast center includes metrics obtained using adjoints of the assimilation and forecast model systems (Langland and Baker 2004). In as complex a computational environment as data assimilation, methods such as the latter are necessary for sorting and making sense of the vast sets of information that can be produced.

Forecasts, particularly at day 5, are often used rather than examination of analyses themselves because, given that the analysis is the best representation of the atmospheric state at some particular time and that it has already incorporated most of the best available observations, there are little additional independent data available that are expected to accurately describe the true atmospheric state. Since forecast errors due to analysis errors grow with time, these can be used to increase the signal of the analysis error with respect to the noise of the estimate of the validating state. Although the presence of model error confounds this interpretation, the technique is widely and successfully used. Indeed, no data assimilation validation is considered adequate without an accompanying examination of subsequent forecast errors.

For the assimilation of clouds and precipitation, error metrics in addition to means and variances are required if results are to be properly understood so that further progress can be fostered. Measures and their interpretation require consideration of the temporal intermittency of clouds and precipitation, the nonnormality of usual quantitative measures (such as precipitation rate), and the representativeness of validating observations (e.g., horizontal undersampling by rain gauges or vertical undersampling by elevated radar beams). If such assimilation improves the forecast strength of a tropical cyclone but it remains wrongly located, an error mean or variance may be worsened, yielding a misinterpretation of the result. While improvements in any field may be so obscured, the problem is exacerbated for the more intermittent fields. Validation is required not only, for example, for cloud water contents and surface precipitation but also for specific characteristics of the hydrometeors, such as size and shape distributions, that affect the radiance transmission, attenuation, and reflection inferred to match observations. Validation should be performed in terms of fits to observed radiances as well as fits to analyses. Many of the useful radiances that are currently ignored by the analysis (e.g., due to limited data selection) can be used as independent data for validation purposes. A variety of metrics are therefore required, including some new ones yet to be defined.

Validations need to be performed using independent observational datasets [e.g., radar measurements from experimental missions such as Tropical Rainfall Measuring Mission (TRMM) or CloudSat] even when the representativeness of these data may be limited. The focus should be on model variables describing the hydrological cycle, the most critical one being atmospheric water vapor. Internal diagnostics of data assimilation systems evaluated for wind, temperature, and surface pressure should be extended to the humidity variable (Andersson 2004; Talagrand 2004). New validation techniques have to be explored to circumvent some of the above issues (e.g., using object-oriented approaches and scale-dependent techniques).

7. Summary

Studies regarding the assimilation of cloud and precipitation observations initiated more than 20 years ago have led to operational implementations at several weather forecasting centers. Indeed, such assimilation is exceptionally difficult compared to assimilation and prediction of the dynamical fields. Despite this encouraging progress, a number of outstanding issues have been reviewed in this paper. Most of these issues are rather fundamental, meaning that they are unlikely to loose their relevance by simple introduction of a new observation type or assimilation technique.

It remains unclear what the impacts of some of these issues are and how critically they require addressing. All are unlikely equally important but, if only because of their fundamental natures, all deserve some consideration. Those for which no investigative resources exist should at least be noted and their potential effects monitored. When they are instead simply ignored, with reports of significant progress stated nonetheless, the experimental designs, control comparisons, skill measures, and interpretations should be deliberately examined.

Some of the issues concern problems that are already considered somewhat solved, such as dynamical balance of large-scale flows and general predictability. Since the context of assimilating clouds and precipitation is notably different, however, even these "solved" problems likely require revisiting. The condensation of water, for example, is most sensitive to characteristics of the analysis fields that are distinct from those that prescribe the synoptic-scale dynamical patterns.

The generality of already-reported results with respect to different models, measures, and synoptic conditions must be verified. Most of the past studies have been limited, considering the ranges of model- and case-dependent behaviors regarding cloud systems that exist. Some studies have also focused on improvement of a particular data assimilation system rather than revealing behaviors or results expected to be general. This remains the motivation for most data assimilation development and corresponding supported research.

Several of the issues can be investigated as isolated components of the complete data assimilation problem. In fact, for many, examining them as isolated components may yield greater understanding than attempting to ascertain their effects within a complete, highly complex, data assimilation system. Researchers to whom such complete systems are unavailable can therefore nevertheless seriously investigate the cloud and precipitation assimilation problem. For them, what remains critical, however, is that the complete problem be sufficiently understood so that the results and their interpretations of the isolated context equally apply to the larger one. Since many critical aspects of the larger problem are currently known by only a few developers and are scantily published, efforts to educate, communicate, and collaborate must therefore be enhanced.

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