A POORMAN'S 4DVAR: THE USE OF ADJOINT MODEL IN AN INTERMITTENT DATA ASSIMILATION SYSTEM

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Abstract

A highly simplified 4-dimensional variational data assimilation (4DVAR) system is formulated aiming at an early operational implementation on current supercomputers. The system is a hybrid system based on both an intermittent data assimilation, including an Optimal Interpolation (OI) analysis scheme, and a 4DVAR setup. The idea is to use the adjoint model to produce an improved first-guess for the OI scheme. A 5 day data assimilation is chosen to demonstrate the applicability of our method. It is shown that the analysis increments are reduced and the forecast of a rapid cyclone development is improved.

1 Introduction

Many meteorological data assimilation systems in operational use today rely on the optimum interpolation method (OI) (Eliassen, 1954; Gandin, 1963) applied at fixed analysis times. Time continuity is obtained by using a forecast from the previous analysis time as a first guess field for the optimum interpolation. A new method, four dimensional variational data assimilation (4DVAR), was first suggested by Le Dimet and Talagrand (1986) and by Lewis and Derber (1985). The main idea is to use observations over a finite time interval to compute an optimal initial state for a numerical forecast model. The 4DVAR technique ensures an initial state where the time development of meteorological systems is handled consistently with the dynamics of the forecast model. A main shortcoming of OI in an intermittent data assimilation system is that rapidly developing systems may be damped because the analysis increments in standard OI

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are equivalent barotropic for single level observations. Most rapidly developing mid-latitude meteorological systems have a pronounced baroclinic tilt which cannot be described by barotropic theory. A preliminary attempt to take some of the baroclinic developments into account in an intermittent OI based system is described by Bengtsson (1980).

The 4DVAR idea has been pursued at several meteorological forecasting centers (Thépaut and Courtier, 1991; Zupanski, 1993) but a clear disadvantage with a full 4DVAR system is the immense amount of computing time which is needed for data assimilation. Comparing with the computing time needed for the actual forecast, the originally proposed 4DVAR technique requires about 100 times as much computer time. Recently Courtier *et al.* (1994) have proposed an incremental technique which drastically reduces the required computing resources. In an incremental system it is, however, assumed that observations are handled with the same technique as in a full 4DVAR system both with respect to interpolation etc. and with respect to quality checking. One advantage with present OI schemes is the extensively tested technique for quality checking which has been developed (Lorenc, 1981; Hollingsworth and Lönnberg, 1986). The variational assimilation approach has potential for application of powerful quality control algorithms as well (Lorenc and Hammon, 1988), but these have not yet been tested within a fully operational framework.

In the present study we will describe a system which is basically a conventional intermittent, OI based data assimilation system but where we use the adjoint model from a 4DVAR system to improve the assimilation of rapidly developing baroclinic structures. This is achieved by iterating the OI analysis in a cyclic fashion where the first guess field is improved in each cycle by adjusting the initial state for the first guess forecast using the adjoint model. This technique has been used to demonstrate the sensitivity of forecasts to small perturbations in the initial state (Errico and Vukicevic, 1992). The idea to improve a forecast by using an analysis at some later time into the forecast was first proposed by Rabier *et al.* (1996) using a global model. Gustafsson and Huang (1996) have demonstrated that this idea also works in a limited area model over a shorter time interval. Here we will show that in a pre-operational environment the technique used in sensitivity studies improves the first guess fields leading to a consistent improvement of analysis and forecast quality over a 5 day data assimilation period.

A vital component of a 4DVAR system is the adjoint of the forecast model. In this study we will use the HIRLAM forecasting system and its adiabatic adjoint which is described in Gustafsson and Huang (1996). The technique which we propose is the following (Poorman's variational assimilation, PMV) where it is assumed that the analysis time is 0 and the length of the assimilation window is 6 h:

(1) Starting from t=-6 h, the nonlinear forecast model including physics is integrated forward to produce the preliminary first-guess field at t=0.

(2) With the observations at t=0 and the preliminary first-guess field, an OI analysis is performed which results in a preliminary analysis.

(3) Using the difference between the preliminary first-guess and the preliminary analysis as input to an energy-related quadratic cost-function, the gradient of the cost function with respect to forecast model variables is calculated and the adjoint model is integrated backward in time to produce a sensitivity increment field at time t=-6 h. The cost function is calculated over the entire forecast domain with relaxation toward zero along the lateral boundaries. Moisture is not included in the quadratic cost function.

(4) Adding the sensitivity increment field to the analysis at t=-6 h, the nonlinear forecast model is integrated forward in time (sensitivity forecast) to produce a new first-guess.

(5) The final OI analysis is performed based on the new first-guess and the same observations.

The backward (adjoint) and forward (forecast) cycle, steps (3)-(5), can also be repeated. There is, however, no guarantee that an iterated procedure will converge. The suggested non-iterated scheme violates in principle the assumption made in OI that first guess and observation errors are independent. This problem is further discussed in section 4. An iterated scheme certainly makes this violation of the OI asssumptions more severe. The computer time required for one cycle (steps 1-5) is about 5 times that required for one OI analysis.

The major motivation for this technique is the ability of the backward adjoint and forward non-linear integration cycle to act as a dynamical filter on the preliminary OI analysis increments. It was demonstrated by the aforementioned sensitivity studies, that unstable forecast error modes may be captured by this procedure. The analysis increments of the final OI analysis application are smaller and, consequently, the ensuing forecast may be associated with a less serious spin-up of e.g. baroclinic structures. Our aim is thus to improve those forecasts where large preliminary analysis increments, dominated by equivalent barotropic structures, damp strong baroclinic developments.

A distinct advantage of our proposed simplified 4DVAR scheme is that we are able to make early use of important dynamical benefits of 4DVAR, since we do not need to wait for the development of the complex software for observation handling and the background error constraint, needed for full, as well as incremental, 4DVAR.

2 Experiment setup

In order to test the idea described in the previous section, the high resolution limited area modeling (HIRLAM) system is used. The HIRLAM system is developed in a joint Nordic-Dutch-Irish research project (Machenhauer, 1988; Gustafsson, 1993). It is an intermittent data assimilation system including an optimal interpolation (OI) analysis scheme and a forecast model. A brief description of the data assimilation system, including the grid point HIRLAM model and model parameters, can be found in Huang *et al.* (1994). The spectral HIRLAM model, the initialization method and the adiabatic adjoint model are described in Gustafsson (1991) and Gustafsson and Huang (1996).

The operational HIRLAM setup is given in Figure 1 if the shaded part is excluded. At the analysis time (e.g. t=0), based on the first-guess field from the previous data assimilation cycle (FGS00, a 6 h forecast) and the observations collected in the data window from -3 h to +3 h (OBS00) the OI scheme gives the analysis field (ANA00). Starting from the analysis field (ANA00), the forecast model (**fom**) produces the operational (+36 or +48 h) forecast which includes the first-guess field to the next data assimilation cycle (here FGS06).

The method proposed here adds an extra component to the above system, based on variational data assimilation principles. The modification is given by the shaded area in Figure 1. Using the preliminary analysis (ANA00) as a "truth (or observation)" and the preliminary firstguess (FGS00) as a "guess", a backward adjoint model integration (**adm**) produces a gradient field valid at -6 h (GRD18). Subtraction of a fraction of the gradient field from the analysis at -6 h (ANA18), the forecast model (**fom**) produces a new firstguess (FGS00*). If the fraction is too large the six hour forecast will overshoot while a too small fraction will not produce the required effect. The value 20 % is chosen based on experience with sensitivity forecasts in Gustafsson and Huang (1996). Using the same observation (OBS00) again but with the new firstguess (FGS00*), the OI scheme (**ana**) produces a new (final) analysis (ANA00*).

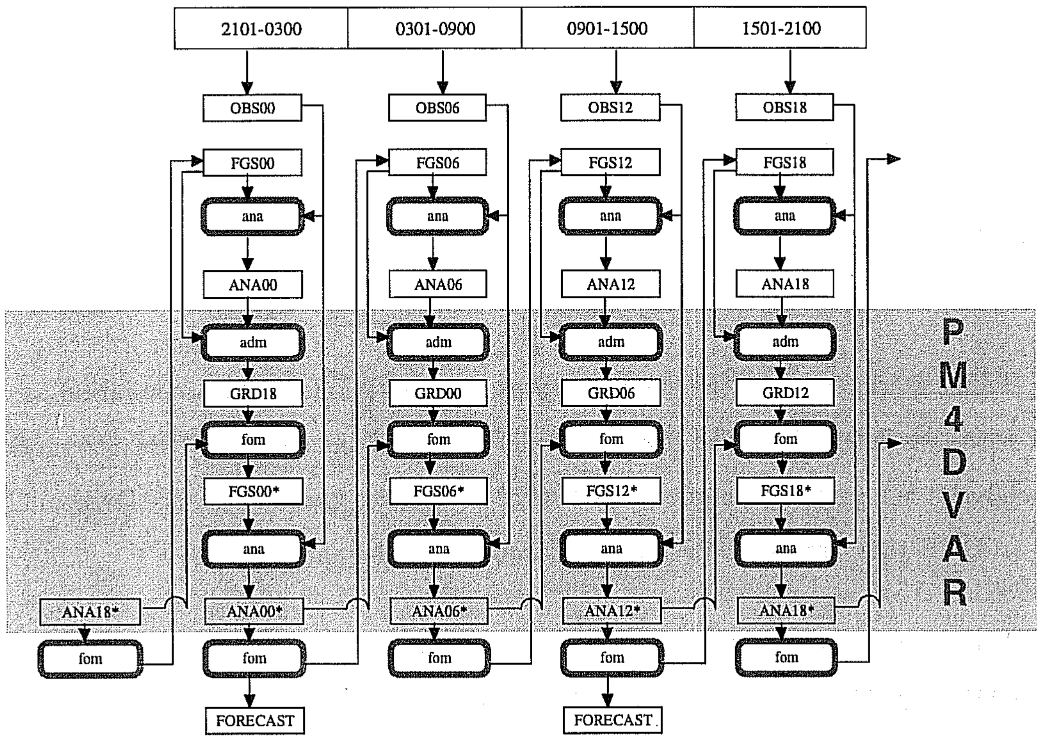

Figure 1: Data flow for the HIRLAM operational data assimilation system (without shaded part) and for the poorman's 4DVAR (with the shaded part).

In the operational setup, the boundaries for the HIRLAM model forecast are obtained from European Centre for Medium-range Weather Forecasts (ECMWF). These boundary fields have been produced with analyses 12 h before the analysis time or even earlier and can strongly influence the quality of the HIRLAM forecast (Gustafsson, 1990). In this study we are mainly concerned with analysis problems in the interior of the model domain. Therefore, to reduce the effect of old boundaries, analyzed boundary fields are used in this study. These analyses have been produced by running the Danish Meteorological Institute (DMI) operational HIRLAM model on the same grid mesh and for the same period. This model and its analysis are referred to as DKH.

A 5 day period, 0000 UTC 13 Sept 1994 - 0000 UTC 18 Sept 1994, has been chosen for the data assimilation experiments. The DKH analyses of the mean sea level pressure for this period are given in Figure 2. The synoptic situation is characterized by an intense development of a low pressure system in the middle of the period. In the beginning of the period, 0000 UTC 13 Sept 1994, a small low pressure system was over the Atlantic ocean, south-west of Ireland. This system developed into a major cyclone which hit Denmark and Southern Sweden three days later. At the end of the 5 day period, the cyclone was significantly weakened. This period was also chosen for the sensitivity study by Gustafsson and Huang (1996).

Two data assimilation experiments over this 5 day period using the DKH analysis as lateral boundaries are discussed in this paper:

OIA: This experiment uses the same setup as the operational data assimilation system DKH with two differences. The forecast model in OIA is the spectral HIRLAM model while in DKH it is a grid point model. The lateral boundaries used in OIA are DKH-analyses while in DKH they are ECMWF forecasts available at the analysis time.

PMV: This experiment uses the proposed technique discussed above. The only difference between PMV and OIA is the shaded part in Figure 1. The forecast model is the spectral model. The lateral boundaries are DKH-analyses. The adjoint model is adiabatic but includes horizontal diffusion. The length of the backward adjoint and the forward forecast runs is 6 h. The changes to the initial model state is 20% of the cost function gradient, which is obtained by the adiabatic adjoint model run.

In the PMV assimilation experiment, the OI analysis scheme is applied twice for each analysis time to the same observations without any change to the first guess and observation error structure functions. It may be argued that the first guess errors should be reduced relative to the observation errors in the second OI analysis as the modified first guess is closer to the observations than the first one. It may also be argued, however, that the adjoint and forward model integrations act as a dynamical filter, projecting the preliminary, equivalent barotropic, analysis increments on to baroclinic structures in the modified first guess. The differences between the two first guess fields may thus be interpreted as being orthogonal to the preliminary analysis increments. If this is the case the error structure functions should remain unchanged. As we have no good estimate to quantify the possible change in the relative error level and because of the arguments above, we have decided to leave the relative error levels unchanged.

The model domain is also chosen as that in DKH, shown in Figure 2. In the very first assimilation cycle, the first-guess field is obtained by a short-range forecast started from a DKH analysis. In order to assess the forecast quality, a 36 h forecast is performed from each analysis (21 forecasts in each data assimilation experiment).

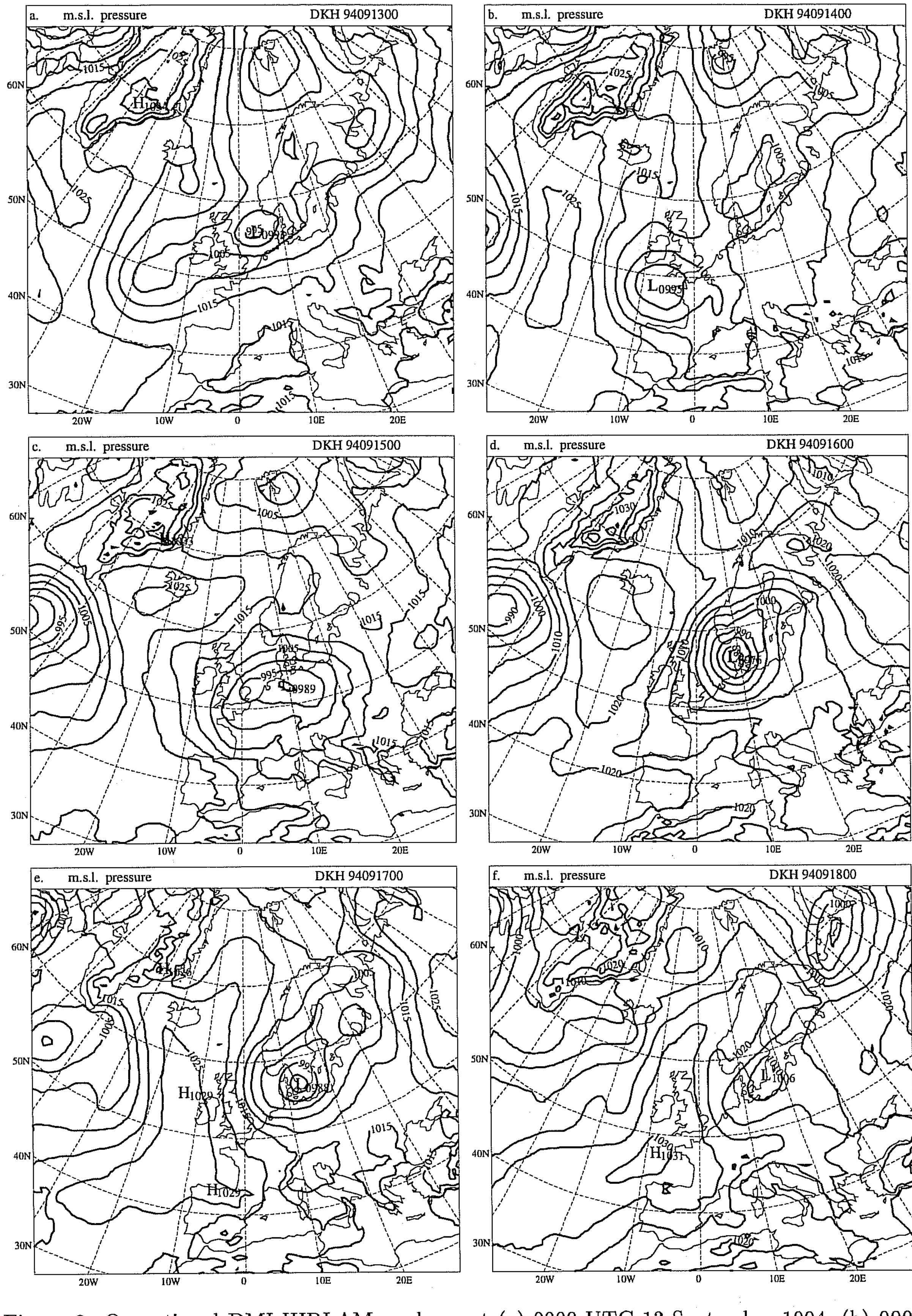

Figure 2: Operational DMI HIRLAM analyses at (a) 0000 UTC 13 September 1994, (b) 0000 UTC 14 September 1994, (c) 0000 UTC 15 September 1994, (d) 0000 UTC 16 September 1994, (e) 0000 UTC 17 September 1994, (f) 0000 UTC 18 September 1994. The contour interval is 5 hPa.

3 Results

3.1 Case study

In order to demonstrate how the PMV system works, the case with the most significant impact is chosen from the 5 day period. This case is the rapid cyclone development between 1200 UTC 14 Sept and 0000 UTC 16 Sept 1994. The operational analysis at the beginning of this period is given in Figure 3a. The low pressure system to be rapidly intensified is initially centered in Brittany with a central mean sea level pressure of 996 hPa.

The OIA analysis is given in Figure 3b. The two analyses in the PMV experiment are given in Figure 3c-d, where ANA1 is the preliminary analysis and ANA2 is the final analysis for the same time. These mean sea level pressure fields all look very similar to the DKH analysis. The main differences are related to mean sea level pressure reductions over Greenland. This is because the orography used by the spectral model (forecast model in OIA and PMV experiments) is smoother than the one used by the grid point model (the DMI operational forecast model) due to the spectral truncation. The difference between the two analyses in the PMV experiment is very small. The maximum difference in surface pressure is only slightly above 1 hPa (Figure 3e). There is almost no significant difference in the region of the low pressure system. The differences between the two 500 hPa geopotential analyses in the PMV experiment are also quite small but, and this is more important, these differences have components in strongly baroclinic structures. This is illuminated by comparing the first guess fields for the two PMV analyses (Figure 4), since these first guess field differences are the direct result of the backward adjoint and forward forecast model integrations. Notice the vertical tilt between surface pressure and 500 hPa geopotential first guess field differences in the area over northern France and Belgium (50N,5E). These differences in the upper-air baroclinic structures are also present in the differences between PMV and OIA first guess fields and presumably the origin of the differences in the ensuing forecasts, to be discussed below.

We first show that the analysis increments are significantly reduced in the second OI analysis. In Figure 5, the analysis increments in horizontal wind components (u,v), temperature (T), specific humidity (q) and mean sea level pressure (MSLP) due to the two analyses are shown as functions of pressure. Both bias and rms differences are given. The reduction in analysis increments is significant in u, v, T and MSLP. The largest changes occur at the jet level. The difference in q increments is small, presumably due to the adjoint model being adiabatic.

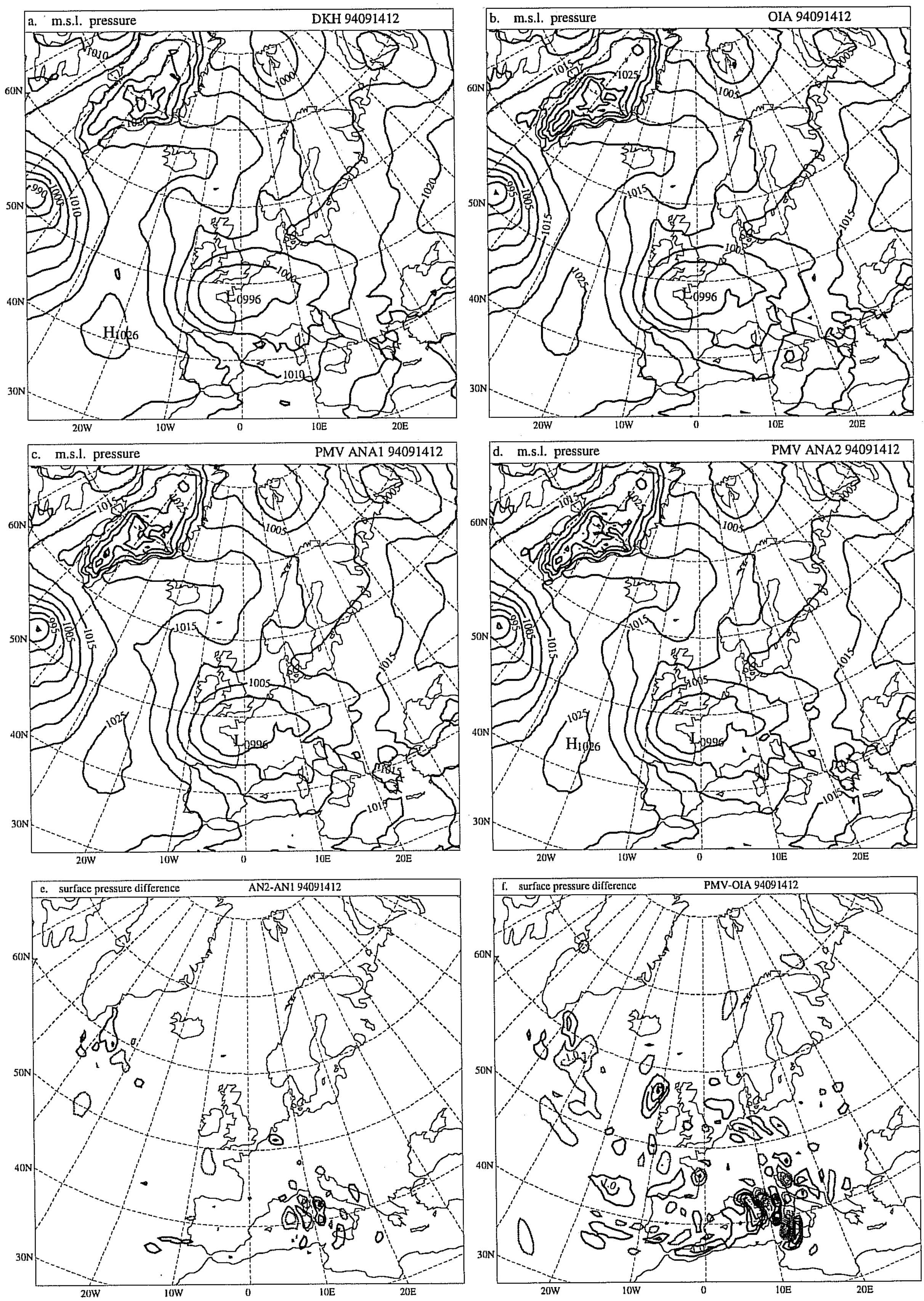

Figure 3: Analyzed mean sea level pressure for 1200 UTC 14 September 1994 from (a) DKH; (b) OIA; (c) PMV, the preliminary analysis (ANA1); (d) PMV, the final analysis (ANA2). The difference map between the two analysis in PMV, ANA2-ANA1, is given in (e). The difference map between the PMV analysis (the same as ANA2) and the OIA analysis is given in (f). The contour interval is 5 hPa in (a)-(d) and 0.5 hPa in (e)-(f). Zero-line is suppressed.

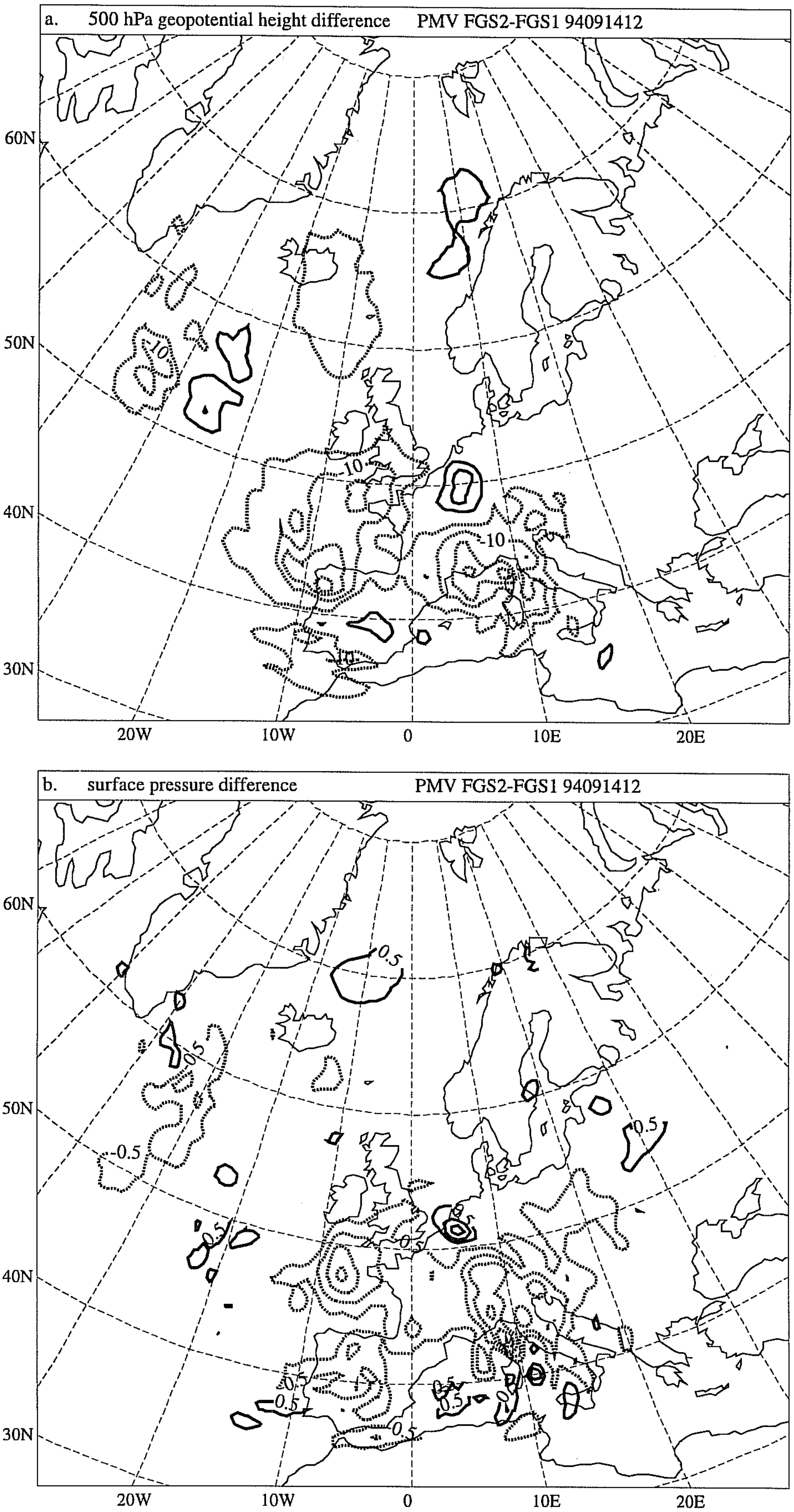

Figure 4: The differences between the 500 hPa geopotential (a) and surface pressure (b) first guess fields in the PMV experiment at 1200 UTC 14 September 1994. The contour interval is 5 dm in (a) and 0.5 hPa in (b). Zero-line is suppressed.

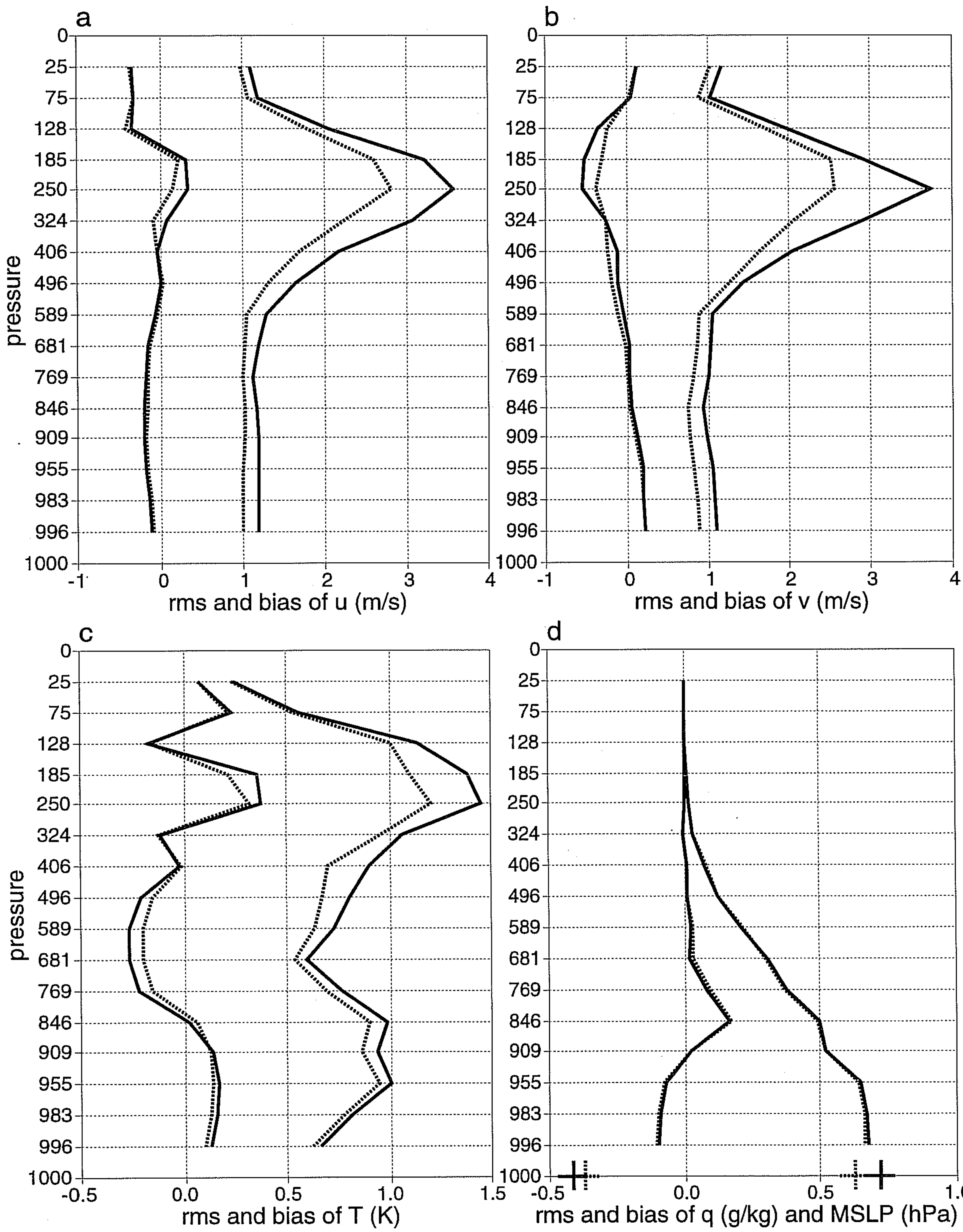

Figure 5: Analysis increments for horizontal wind components u (a), v (b), temperature T (c), specific humidity q and the mean sea level pressure MSLP (d) at 1200 UTC 14 Sept 1994. The full lines are for the preliminary analysis increments (ANA1). The dashed lines are for the final analysis (ANA2). The vertical axis is pressure (at the full model levels, assuming the surface pressure is 1000 hPa). Both bias (curves on the left) and rms (curves on the right) are given. In (d), MSLP values are indicated by crosses.

The main difference between the two analyses is in the upper-air structures, which is similar to what was demonstrated by Gustafsson and Huang (1996) in their sensitivity study. As was indicated above, there is a difference in the the upper-air baroclinic structures between the PMV and the OIA analyses. The impact of these analysis differences may be followed through the amplification of the difference between OIA and PMV sea-level pressure fields during the later ensuing forecasts (Figure 6). These differences are directly related to phase speed differences of the cyclone system in the two forecast runs.

The areas with relatively large surface pressure differences at the analysis time, which are noticeable from Figure 3f, show little dominance in the later forecast differences, which are shown in Figure 6. For instance, the differences at the analysis time over the Mediterranean decrease with time in the forecasts. In addition, although the dominant difference pattern between the two 36 h forecasts shown in Figure 6f can be traced back to 12 h forecasts (from Figure 6f back to Figure 6b), it is difficult to trace it back to surface pressure differences at the analysis time (Figure 3f). These results indicate that the most important improvement of the PMV analysis lies in the upper air structures.

Comparing the two 36 h mean sea level pressure forecasts, one can notice a significant difference in the position of the deep low pressure system. Direct comparisons between forecasts (Figure 7c-d) and their verifying analyses (Figure 7a-b) show that the PMV forecast is significantly better in predicting the low pressure center position than the OIA forecast. The verifying analyses are, as expected, very similar.

The difference maps between the 36 h forecasts and their verifying analyses (Figure 7e-f) also indicate the different positions of the deep low pressure system, the largest negative and positive differences in Figure 7e are -17.3 and 13.5 hPa, respectively, while in Figure 7f they are -8.4 and 10.6 hPa. In other words, the difference between the 36 h forecast and its verifying analysis is much smaller in the PMV than in the OIA experiment. Furthermore, comparing these difference maps, the difference between the two forecasts (Figure 6) also points to the superiority of the PMV forecast. It has managed to recover most of the low pressure position error of the OIA forecast (Figure 7e-f).

To give an objective measure of the forecast quality, the forecasts are directly verified against observations from European radiosonde and synoptic stations (Hall, 1987). The bias and rms errors in the mean sea level pressure forecast are shown in Figure 8 as functions of forecast length

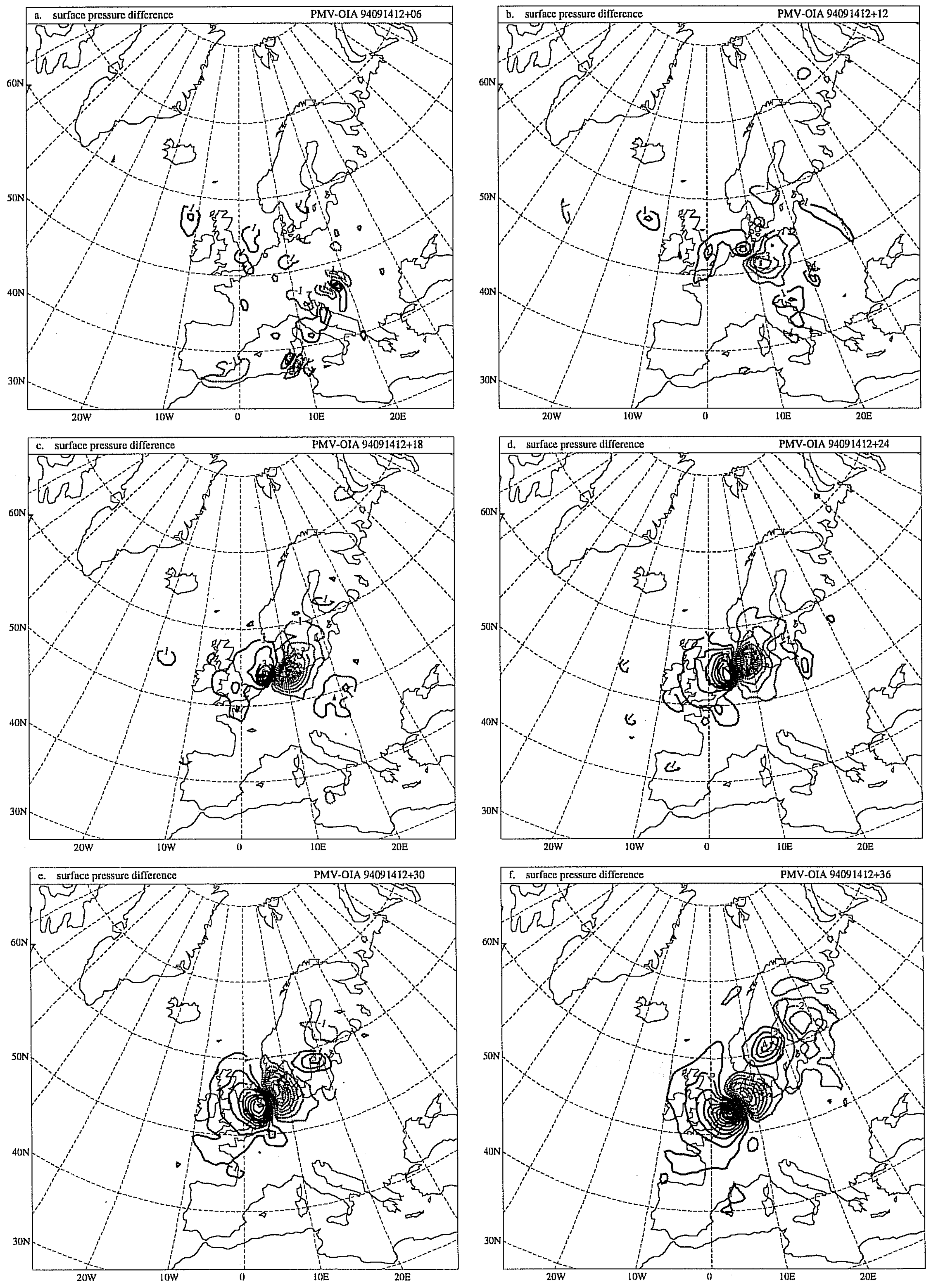

Figure 6: Difference in the surface pressure between the OIA forecasts and the PMV forecasts at (a) +06 h; (b) +12 h; (c) +18 h; (d) +24 h; (e) +30 h; (f) +36 h. The contour interval is 1 hPa. Zero-line is suppressed.

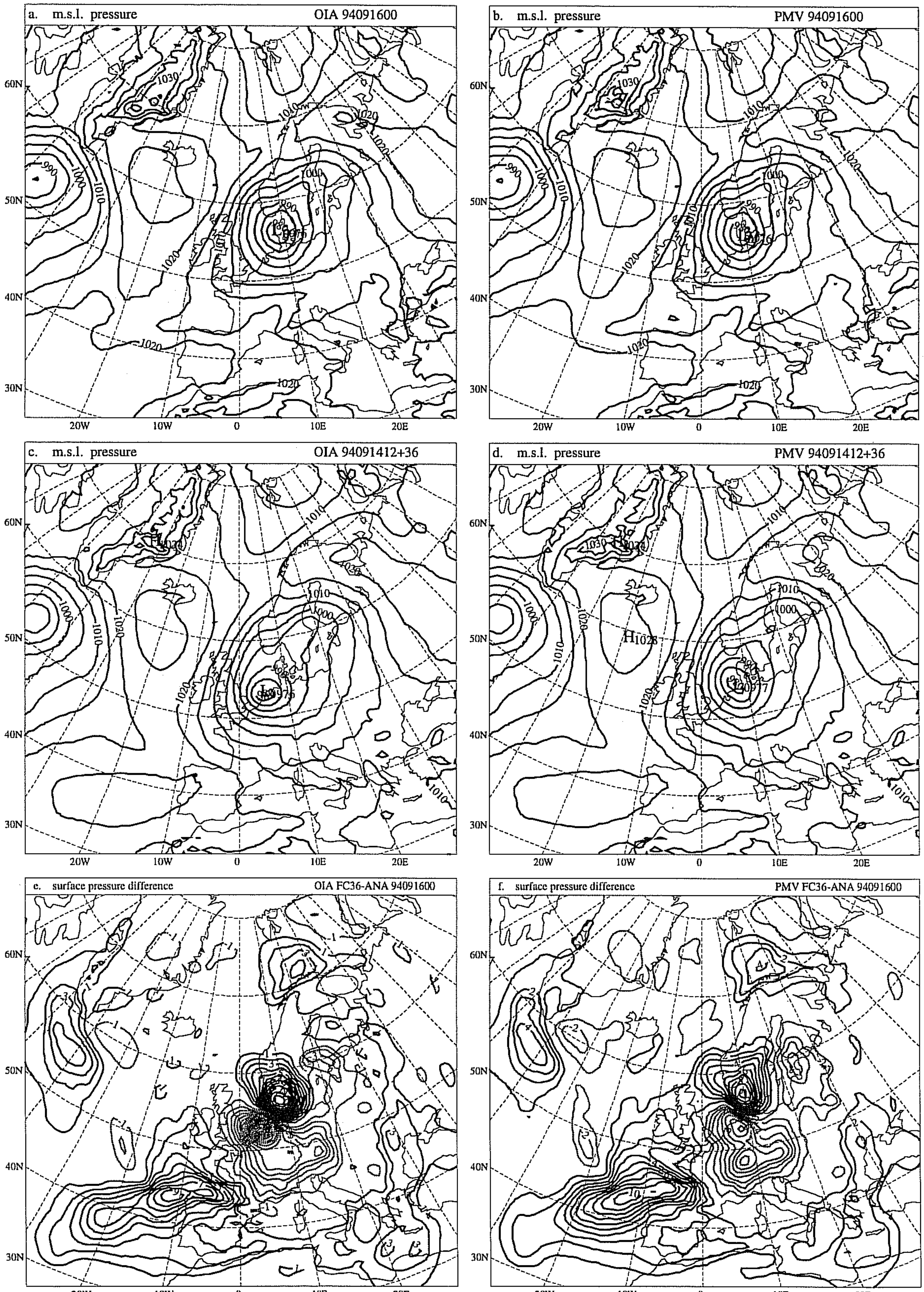

Figure 7: Mean sea level pressure for (a) OIA- and (b) PMV-analyses, 0000 UTC 16 September 1994, (c) OIA- and (d) PMV-36 h forecast from 1200 UTC 14 September 1994, (e) difference between (a) and (c), (f) difference between (b) and (d). The contour interval is 5 hPa in (a)-(d) and 1 in (e)-(f). Zero-line is suppressed.

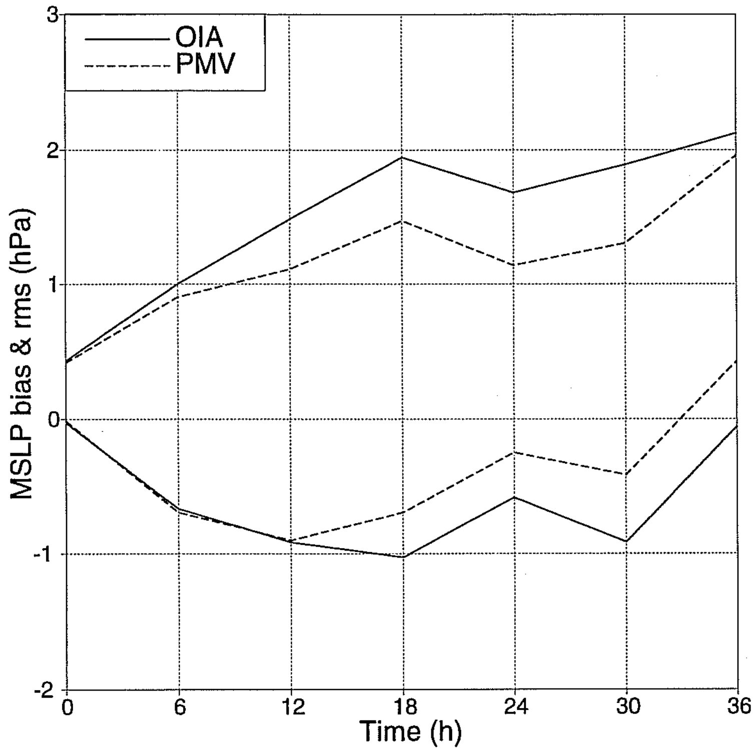

Figure 8: Observation verification of mean sea level pressure as a function of forecast length for OIA (full lines) and PMV (dashed lines) for the 36 h forecasts starting from 1200 UTC 14 Sept 1994. The lower two curves are for the bias. The upper two curves are for the rms.

for this case (a single 36 h forecast in each experiment). It is evident that the PMV forecast is better than the OIA forecast for this field, in agreement with the subjective impression obtained from mean sea level pressure maps and their differences.

3.2 Five day period

In the previous subsection only one case in our 5 day data assimilation period is discussed. The main motivation for showing this case is that we found a significant reduction in forecast error related to an intensifying cyclone. For the entire ensemble of 21 (36 h) forecasts over the five day period the forecast improvement is less dramatic. This is to be expected as the PMV method only gives substantial forecast quality improvements in cases where upper-air structures are not well handled by the OI analysis scheme. It should also be noted that a five day period is too short to present conclusive evidence that the proposed method could be implemented operationally. A five day period is, however, more convincing than just one case and does not require an overwhelming amount of computer time.

The only verification parameter discussed in the previous section is mean sea level pressure as this was considered to be sufficient to demonstrate the impact of our method. Many other variables (e.g. wind and temperature) and other analyses/forecasts (totally there are 21 analyses and forecasts in the 5 day data assimilation period) have been examined. The results are summarized by the observation verifications in Figure 9. Both bias (lower two curves in each panel) and rms (upper two curves in each panel) are shown as functions of forecast length. The values are averaged over all 21 forecasts in the 5 day data assimilation period. Twelve parameters are chosen as in the DMI operational setup: geopotential height Z, temperature T, wind vector V at 250 hPa, 500 hPa, 850 hPa, mean sea level pressure (MSLP), 2 meter temperature (T02M) and 10 meter wind (V10M).

Averaged over 21 forecasts, MSLP verification scores (Figure 9j) remain similar to those from the case study (Figure 8). The PMV forecasts are consistently better than the OIA forecasts in MSLP and geopotential height of 850 and 500 hPa. It seems difficult to draw a general conclusion for other parameters. Only looking at the 36 h forecasts, PMV has better scores in almost all parameters. Through the 36 h forecast range, the improvements are found in the geopotential height at all levels and in the 500 hPa temperature. In other parameters, OIA and PMV show comparable scores. In particular the wind verifications show little or no improvement using the PMV technique. We have no clear picture of the reasons behind this, one possible explanation may be that upper level wind observations are not particularly plentiful in the rather small area where the forecasts differ significantly. This also applies to upper level temperature and height observations. The surface pressure observations are considerably more plentiful. For surface wind and temperature we do not expect to see much of an improvement as the initial error level is very high and the error growth rate is low.

4 Conclusions

In this paper, a highly simplified (poorman's version) 4-dimensional variational data assimilation system, PMV, is formulated aiming at a cheap and early operational implementation on current supercomputers. The system is a hybrid method based on both an intermittent data assimilation, including an OI scheme, and a 4DVAR setup. The idea is to use the adjoint model to produce an improved first-guess which leads to an improved OI analysis.

Two data assimilation experiments, OIA and PMV, have been run in parallel over a 5 day

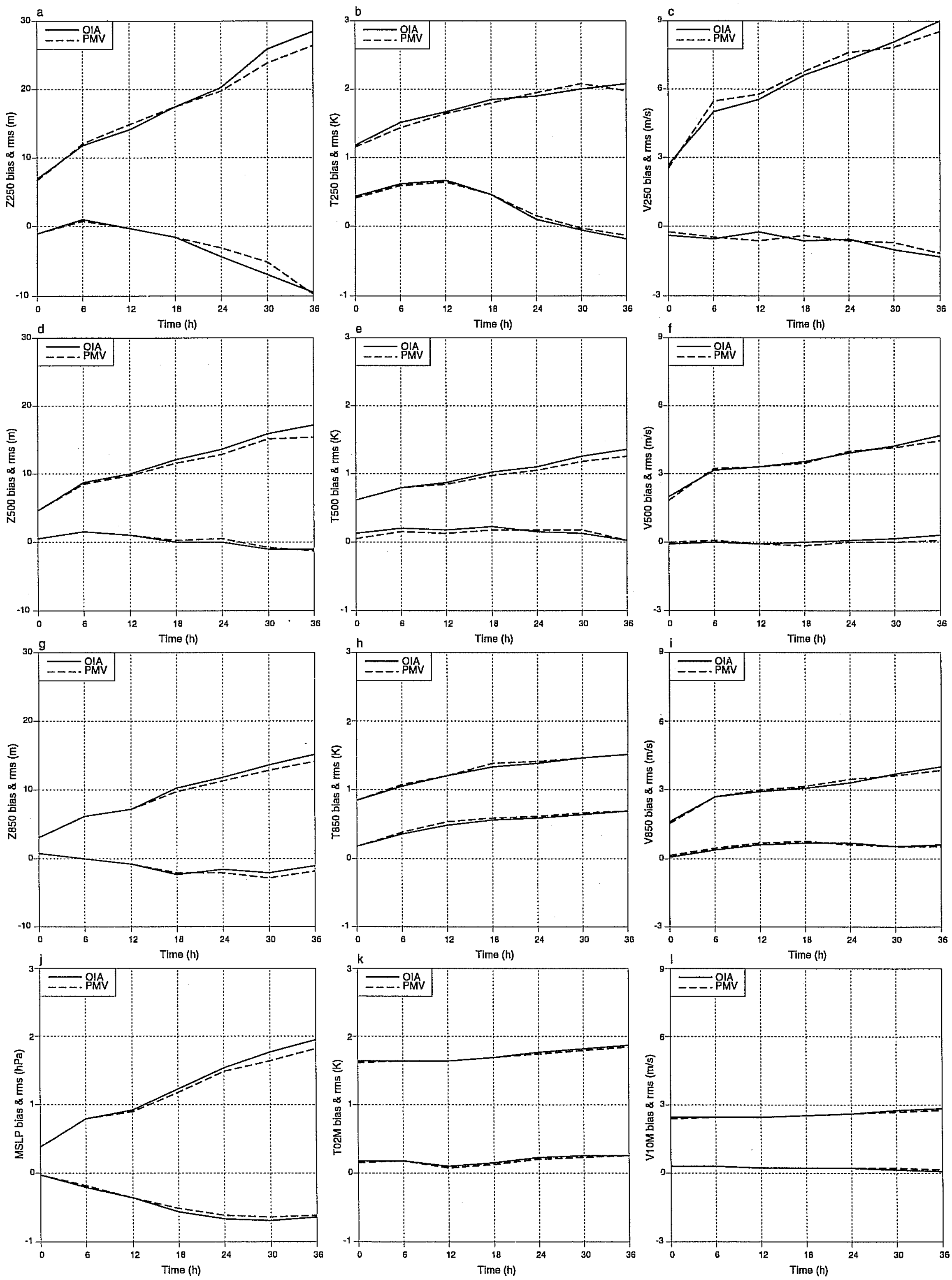

Figure 9: Observation verifications, bias and rms, as functions of forecast length for OIA (full lines) and PMV (dashed lines) over the 5 day period (13-18 Sept 1994). (a) 250 hPa height (d) 500 hPa height (g) 850 hPa height (b) 250 hPa temperature (e) 500 hPa temperature (h) 850 hPa temperature (c) 250 hPa wind (f) 500 hPa wind (i) 850 hPa wind (j) Mean sea level pressure (k) 2 meter temperature (l) 10 meter winds.

period to investigate the impact of PMV on analyses and forecasts. The results can briefly be summarized as follows:

- The PMV analysis increments are smaller than those of OIA, implying that the modified first guess in the PMV experiment is closer to the observations. With regard to validation of the analyses, we are within the observation error and we cannot conclude that we are closer to the truth.
- The upper-air baroclinic structures have been improved by running the adjoint model backward in time and the forecast model forward in time. This is the major advantage of PMV over OIA. Although this improvement is difficult to demonstrate at the analysis time, the evolution of the difference between OIA- and PMV-forecasts clearly points to the superiority of the PMV-forecasts in this respect.
- The overall performance of the PMV system is considered to be satisfactory based on the observation verification. Over the 5 day data assimilation day period, PMV forecasts are better than or at least comparable to OIA forecasts for all selected variables. Towards the end of the 36 hour forecasts there is a general gain in predictability time of about 6 hours.

The PMV system needs a backward adjoint model run (costs roughly twice as much as the forecast run), an extra forecast run and an extra OI analysis. Using the operational system as a reference, the OI scheme costs about the same as a 6 h forecast in computer time. The PMV system, therefore, costs about 5 times the original OI scheme which is equivalent to the computing cost of a 30 h forecast. With only a doubling of the computer power, the PMV system as sketched in Figure 1 is feasible to run operationally with the current model resolution. This is much cheaper than a full 4DVAR implementation which needs more than 100 times the computer time of the OI scheme. However, it should be noted that the PMV system is not much cheaper than the incremental 4DVAR suggested by Courtier *et al.* (1994). A major advantage of our method is, however, that it utilizes all the quality control algorithms and robustness of a well developed OI system. At the same time it removes, at least partly, one of the main drawbacks of OI namely its inability to handle baroclinic structures. It may furthermore be possible to reduce the cost of the PMV, e.g. by running the backward adjoint model integration at a coarser resolution (incremental PMV).

In the OI scheme, it is assumed that the errors of the first guess field and the observation errors are independent of each other. In the PMV setup, this assumption will not be strictly valid. The first guess field of the final OI analysis is a result from an adjoint model integration backward in time and a forecast model integration forward in time. The observations have been used to initiate the adjoint model run. Therefore, the first guess errors of the final OI analysis are, in principle, already influenced by the observation errors. The changes introduced by the adjoint model and the forward forecast model runs are mainly baroclinic, however, while the changes due to OI analysis are more barotropic, in particular if surface observations are available only. Thus, the orthogonality between the barotropic and baroclinic modes has a tendency to alleviate the problem due to the violation of the independence assumption in the OI scheme.

As shown in Gustafsson and Huang (1996), sensitivity forecasts can be improved with more iterations. The quality of the PMV analysis and forecast may also be improved by repeating the PMV cycles. However, there is a difference between the sensitivity forecast and the PMV analysis. In the sensitivity forecast, the analysis is considered as the *final* "truth". The iterations of backward/forward integrations will in principle converge towards the analysis. In the PMV setup, the analysis is only considered as a *temporary* "truth" within one iteration. A new analysis is produced by each PMV iteration. It is therefore difficult to guarantee the convergence of the iteration. The rapid increase in computing time obtained with an iterative scheme also makes us reluctant to proceed in this direction.

The adjoint model used in this study does not contain any diabatic processes. As one of the consequences, the analysis increments in humidity remain almost untouched. The impact of physical processes in the adjoint model upon the PMV analysis and forecast is difficult to assess. The development of the diabatic adjoint is needed to evaluate this aspect of the system.

Another possible improvement of the first guess field is to use a longer assimilation window as demonstrated in the sensitivity study (Gustafsson and Huang, 1996). Since the PMV system is designed for real forecast applications, an increase in data assimilation window length means an older first guess field. Two additional experiments with a 12 h assimilation window, OIA12H and PMV12H, have also been conducted in parallel. The qualitative conclusions are the same as stated above. The verification scores for PMV12H have been improved more over OIA12H than that for PMV over OIA, but they are not getting better than PMV due to the older first guess fields. It may also be argued that through data assimilation cycles PMV can capture some unstable modes which need longer time (*e.g.* 12 h) to grow. In other words, the actual time for breeding the most unstable mode in PMV is longer than the data assimilation window.

After completing our study we have learnt that a similar investigation with a global model has been done by Pu and Kalnay (personal communication). They use a 24 hour interval rather than a 6 hour interval and they test different methods for computing the initial perturbation in the iterated first guess integration. They also find a consistent forecast quality improvement which is even more significant in the Southern Hemisphere than in the Northern Hemsiphere. Even if a longer assimilation window is used we feel that our results with a limited sample are strengthened by the results of Pu and Kalnay (personal communication). For a global model and the medium range a 24 hour assimilation window may be necessary, but as discussed above we have found that a 6 hour window is sufficient for our regional application.

5 Acknowledgments

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