Methods for high resolution analysis

Nils Gustafsson
Swedish Meteorological and Hydrological Institute

1 Introduction

The purpose of this paper is to review methods for high resolution objective analysis with special emphasis on analysis methods applied in numerical weather prediction. The first part of the paper discusses general issues, such as the range of spatial scales, the degree of isotropy, the degree of stationarity and balance conditions. One outstanding problem is the increasing lack of observed data when we go towards higher resolution analysis. Following this general introduction, some operational analysis and data assimilation schemes used for high resolution numerical weather prediction are reviewed and discussed. Various schemes for objective analysis applied for meso-scale case studies and for nowcasting and very short-range weather forecasting are also briefly reviewed. Some experiences from the developement of a data assimilation scheme for a common Nordic/Dutch high resolution forecasting system are finally described and discussed.

2 A discussion on general problems in high resolution analysis

2.1 Scales and structures

A key problem for objective analysis in general is the question of what spatial scales to be analyzed. In terms of the generally utilized optimum (statistical) interpolation technique [14] these spatial scales are defined by a spatial correlation function. The definition of a proper spatial correlation function has sometimes been overlooked and spatial correlation functions like the Gaussian were often utilized in many operational applications, not so much for its spatial spectral characteristics, but rather for practical computational reasons. The importance of a good selection of correlation functions was recognized early by e.g. Julian and Thiebaux [18]. Due to recent findings by Hollingsworth and Lönnberg ([17] and [23]) at ECMWF, the importance of a proper selection of spatial correlation functions is today fully recognized and most operational forecasting centers apply spectrally well based structure functions. In order to analyze all the required scales properly, it is also necessary to select data influencing the grid-point values in such a way that all scales are represented (or to avoid the data selection problem). This requires, however, a large number of observed predictors for each gridpoint to be analyzed. In order so save computing time it is necessary to make certain computational shortcuts like in the ECMWF analysis [24] by letting several gridpoints share the same observational predictors. Another possibility is to let the analysis work as a two-step procedure with different analysis methods used for analysis of large and small scales. This is done in the French high resolution Péridot forecasting system [13]. The weather service of Japan has tested a two-step procedure for analysis of tropical cyclones [21]. In a first step, small-scale (bogus) information on tropical cyclones is introduced into the analysis first guess fields with proper meso-scale structures and in a second step synoptic scale information is introduced with a synoptic scale analysis.

As we go towards higher resolution analysis, several questions related to basic assumptions in the structure function formulations arise. An-isotropy certainly should be taken into account when we want to analyse smaller scale phenemena like frontal zones. One way to proceed is to to formulate flow-dependent (and thus non-stationary) and an-isotropic analysis structure functions. Certain attempts have been made to use ad hoc formulated flow-dependent structure functions for analysis of humidity ([2] and [13]) by elliptic-shaped structure functions elongated in the direction of the frontal zone in the analysis first guess field. Another trial to model an-isotropy, e.g. land/sea effects, within the analysis of near-surface parameters was tried in the Swedish PROMIS-project [1]. Jørgensen [19] managed to detect and model baroclinically tilting structure functions by studying empirical ECMWF forecast error covariances, stratified according to flow type.

We know that forecast models are good at simulating an-isotropic structures like fronts, provided the large scale forcing for the frontogenesis is correctly defined. An alternative to the use of statistical an-isotropic structure functions would therefore be to try to change this large-scale forcing until the forecasted front is in agreement with observations. This requires, however, a fourdimensional analysis including the constraint of a forecast model. Variational analysis including adjoint model techniques are very promising tools being developed at present (see companion papers in this volume). It is most likely, that the application of these four-dimensional data assimilation techniques will replace the need for development of statistically based flowdependent structure functions.

2.2 Balances and adjustment processes

Another important problem in high resolution analysis and data assimilation is the question of adjustment processes and balances. The application of partial geostrophic balance in the (small) analysis increments and the use of the non-linear normal mode initialization are well established in synoptic scale data assimilation. More fundamental research is certainly needed in order to establish proper balance conditions, to be used for analysis as well as for initialization for smaller scale data assimilation.

The questions of balances and adjustment are closely related to the questions of temporal resolution of the analysis and model spin-up. For higher resolution data assimilation we need to increase the frequency of analysis cycles in order to be able to analyse higher frequency meteorological variations by e.g. going from 6 hour assimilation cycles to 3 hour assimilation cycles or even to continuous data assimilation. If we do so, however, we will have problems with the analysis destroying balances established by the model and the decreased data assimilation cycle will not allow the model to re-establish these balances.

2.3 Lack of observations and quality control

Increasing the frequency of data assimilation cycles will also magnify the problem of using single level data. As an example, at 03UTC, 09UTC etc. we mainly have observed surface data and aircraft data available in addition to satellite data. A proper utilization of single level data will require more advanced and dynamically sound structure functions than those used today employing e.g. the assumption of vertical-horisontal separability. These result in too barotropic analysis increment structures when no complete three-dimensional observations are available. Again, flow-dependent structure functions is one way to deal with this problem, but four-dimensional data assimilation using the forecast model itself to distribute the observed information might be the most promising solution.

The most crucial problem for high resolution analysis is the relative lack of data that increases when we go to smaller scales. Remote sensing data, e.g. satellite soundings, satellite image data, radar data and wind profiler data with high temporal resolution, are the possible sources of data to fill in holes between the sparse conventional observational sites. The utilization of these data will require research efforts to interprete the raw data signals into model parameters. The best way to do this interpretation is probably through the forecast model itself. As an example, precipitation data determined from satellite image data, should be used directly to tune the model state (divergence, water vapour and cloud liquid water) to produce the same precipitation amounts. To do this efficiently, four-dimensional data assimilation techniques are probably needed.

The relative sparseness of observed data for higher resolution analysis also makes the quality control of observations a more difficult and crucial task.

3 Review of analysis methods used for operational high resolution numerical weather prediction

An overview of some existing operational (or near-operational) data assimilation schemes used for high resolution numerical weather prediction is given in Table 1. There are several similarities between the schemes mentioned. Most of the schemes are based on intermittent data assimilation including an objective analysis scheme and a non-linear normal mode initialization scheme [26]. Optimum interpolation is the predominantly utilized analysis technique. The Norwegian analysis scheme,

Country/ scheme	Grid resolution	Assimilation/ initialization	Analysis cycle	Analysis method
U.K. UKMO LAM	75 km	Repeated insertion/ divergence damping	3h-Global analysis at -12h	Univariate OI, geostrophic and hydrostatic corrections (SC scheme is being developed)
France Péridot	35km	Intermittent/ NLNM	12h	3D multivariate OI, Direct use of TOVS radiances
Norway LAM50	50 km	Intermittent/ dynamic	6h	SC approximation to 3D multivariate OI
Sweden SMHI LAM	100 km	Intermittent/ NLNM	6h	3D univariate OI, variational adjustment of mass- and wind-field increments
Denmark DMI LAM	100 km	Intermittent/ NLNM	6h	SMHI scheme, (Modified KNMI scheme is being tested)
Nether-lands KNMI LAM	50km	Intermittent/ Bounded derivative method	3h	3D multivariate OI
ECMWF	Spectral T106	Intermittent/ NLNM	6h	3D multivariate OI
HIRLAM	50 km	Intermittent/ NLNM	6h (3h)	LAM version of ECMWF analysis scheme 3D multivariate OI
U.S.A. NMC Regional Model	150 km	NLNM	6 h Global f.g.	3D multivariate OI
Japan JMA LAM	127 km	Intermittent/ NLNM	12 h	2D multivariate OI and spectral analysis in the stratosphere
Australia Regional model	250 km	Intermittent/ NLNM	12 h	SC scheme (3D multivariate OI scheme being developed)

Table 1: Operational (or near-operational) high resolution data assimilation schemes. (SC=Successive Corrections,OI=Optimum Interpolation, NLNM=Non-Linear Normal Mode initialization)

utilizing the successive correction approximation to 3D multivariate optimum interpolation as proposed by Bratseth [10], is one exception, although this scheme also is based on optimum interpolation theory in the sense that the analysis fields will converge towards the optimum interpolation analysis for a proper selection of analysis parameters.

Some specific features of the U.K. Met. Office data assimilation scheme, the analysis scheme of the French Péridot forcasting system and the baroclinically tilting structure function in an experimental Danish LAM analysis scheme are discussed in more detail below.

3.1 The U.K.Met.Office repeated insertion data assimilation scheme

The U.K. Met. Office fine mesh data assimilation scheme [7] is an intermittent data assimilation scheme with repeated insertion of observed data during each time-step of the data assimilation forecast cycles of 3 hours. If T is the initial time of the forecast, data assimilation is started at T - 12h with a global analysis interpolated to the fine mesh area. Then repeated insertion of obvervations valid at T - 9h is carried during the forecast model integration between T - 12h and T - 9h. Data assimilation cycles are then carried out in the same way for the time intervals between T - 9 h, T

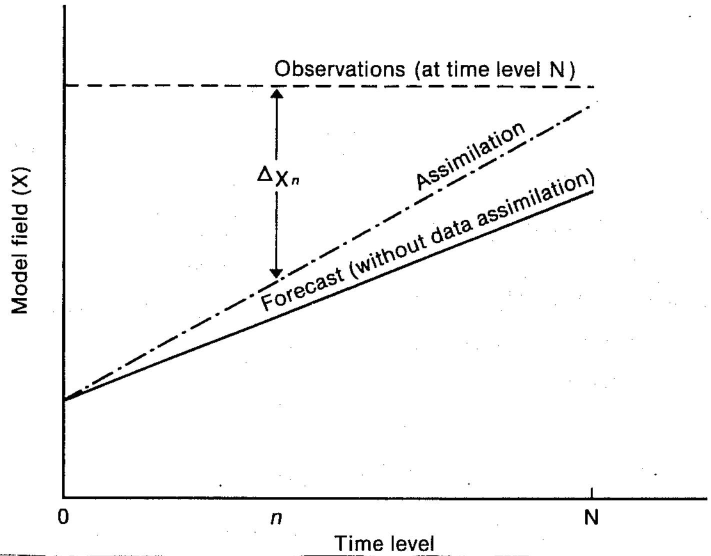

Figure 1: Schematic digram of the assimilation increment in the U.K. Met.Office scheme.

- 6h, T - 3h and T with the observations valid at the end of these intervals.

The basic idea of the repeated insertion data assimilation over a period of 3h with N time steps is schematically illustrated in Figure 1. At every timestep "n" a data assimilation increment ΔX_n is evaluated as the difference between the forecast model state at time-step n and the observed state at time-step N. The data assimilation increment ΔX_n is scaled by a factor χ and added to the forecast model state. For the the fine mesh model this "nudging" factor χ is 0.0 at the start of the data assimilation cycle (time-step 0) and it grows linearly to 0.175 at the end of the data assimilation cycle(time-step N). The aim of this procedure is that the data assimilation state should approach the observed state at the end of the data assimilation cycle.

The assimilation equations in the U.K. Met. Office fine mesh data assimilation scheme can schematically be represented by

$$
\begin{aligned}
\Delta X &= \sum_i W_i(X_i^o - X_t) \\
X'_{t+\Delta t/3} &= A(X_t) + D_d(X_t) \\
X'_{t+2\Delta t/3} &= A(X'_{t+\Delta t/3}) + D_d(X'_{t+\Delta t/3}) \\
X'_{t+\Delta t} &= A(X'_{t+2\Delta t/3}) + D_d(X'_{t+2\Delta t/3}) \\
X_{t+\Delta t} &= B(X'_{t+\Delta t}) + \chi(\Delta X + H(\Delta X) + G(\Delta X))
\end{aligned}
$$

The first equation represents univariate optimum interpolation with interpolation weights pre-calculated in advance of the data assimaltion in order to save computing time. This is possible because of linearity of the optimum interpolation, with values of interpolation weights being only influenced by observation site positions and type of variable.

The A-operator represents forward time stepping of adjustment terms, B advection terms and D divergence damping terms. An enhanced divergence damping was introduced to control the gravity noise (since no initialization is carried out). H represent hydrostatic adjustment of temperature due to analysis increments of surface pressure. These are calculated in such a way that the geopotentials above a certain level are not modied by surface pressure increments. G represents geostrophic wind increments as calculated from the mass field analysis increments.

The U.K. Met.Office is developing a new fine mesh data assimilation scheme utilizing a successive correction analysis. One important reason for this new scheme is the non-necessity to pre-calculate the analysis weights which makes it possible to implement a truely continuous data assimilation with observations inserted repeatedly during a time interval centered around the true observation times.

3.2 The French Péridot analysis scheme

Péridot is the operational high resolution ($\Delta s = 35km$) short-range forecasting system of the French weather service. The analysis scheme of Péridot [13] is based on 3-dimensional multivariate optimum interpolation of forecast errors. Initialization is carried out with a non-linear normal mode scheme. Here we will briefly discuss two unique features of the Péridot data assimilation scheme, the direct use of satellite sounding radiances (TOVS) and the Fourier merging of the Péridot analysis with a coarse mesh analysis.

Input observational data to the Péridot analysis are, in addition to coventional data, TOVS micro-wave and infra-red radiances and histogram analyses of AVHRR pixel data within the TOVS infra-red fields of view. The AVHRR histogram data are used to distinguish clear or near-clear TOVS fields of view, for which TOVS radiances are utilized directly in the mass- and wind-field analysis, from the cloudy areas for which bogus humidity observations are generated.

Deviations between observed radiances and radiances calculated from the forecast model profiles, i.e. radiance forecast errors, are used as predictors in the mass- and wind field analysis. Thus, spatial correlations for radiance forecast errors as well as cross-correlations between e.g. radiance errors and temperature and wind forecast errors are needed. Models for these correlations have been obtained by a Monte-Carlo technique:

- Start from a set of (true) radiosonde profiles of geopotential, temperature and humidity.
- Use forecast error covariances of these variables to generate a number of forecast error profiles being random realizations obeying these covariances.
- Run a forward radiance calculation routine to obtain simulated "true" as well as forecast radiances.
- Evaluate the covariance matrix of the simulated forecast radiance errors of the different radiance channels as well as cross-correlations between radiance errors and errors of geopotential, temperature and humidity.
- Assume the horisontal correlation of synthetic radiance errors to be the same as for temperature forecast errors.

In order to model all the required covariances and cross-covariances it is also necessary to introduce some separation assumptions. As an example, cross-correlations between geopotential errors and radiance errors in different horisontal positions are modelled as a product of a horisontal correlation of the geopotential forecast-errors and the cross-correlation between geopotential error and radiance error in the position of the radiance measurement:

$$r(\epsilon R_i^g(\alpha), \epsilon Z_k^g(p)) = r(\epsilon R_i^g(\alpha), \epsilon Z_i^g(p)) \times r(\epsilon Z_i^g(p), \epsilon Z_k^g(p))$$

Here, $\epsilon R_i^g(\alpha)$ denotes radiance error of channel α in position "i" and $\epsilon Z_k^g(p)$ denotes geopotential error of pressure level p in position "k".

The observational error covariances for the radiance measurements are derived by comparing co-located satellite radiance observations and radiance values determined from radiosonde data. The effect of the radiosonde errors is taken care of by subtraction of a radiance error covariance matrix corresponding to the radiosonde errors, also derived by Monte-Carlo simulation.

A second unique feature of the Péridot analysis scheme is a Fourier merging of the analysis fields with a coarse mesh analysis. First, a lateral boundary component (fulfilling the lateral boundary values, which are the same for the fine-mesh and the coarse-mesh analysis fields and with zero Laplacian) is subtracted and then both analysis fields are transformed by two-dimensional Fourier tranforms. The final fine mesh analysis is then determined by merging the Fourier coefficients, relying more on the coarse mesh analysis for the larger scales and relying completely on the fine mesh analysis for the smallest horisontal scales. The main reason for Fourier-merging with a coarse-mesh analysis is the difficulty to analyze larger horisontal scales with the local data selection schemes in the Péridot analysis, designed to do a good job for the smaller scales, and the lack of observations on larger scales within the relatively small Péridot area.

The Péridot data assimilation has proven to have good impact on forecasts of several significant intensive small-scale weather events as compared to runs of the Péridot forecast model on interpolated coarse mesh analysis fields. Also the use of satellite radiance data in Péridot has proven to give positive impact for selected cases [36].

3.3 Baroclinically tilting structure functions

A multivariate optimum interpolation analysis scheme, originally developed at the KNMI, is being used experimentally at the Danish Meteorological Institute by Jørgensen ([19] and [20]) for testing baroclinically tilting structure functions. Radiosonde minus 6 h ECMWF forecast geopotentials were utilized to determine these structure functions. North American radiosonde stations were selected to get a consistent data set.Only stations from the western part of this area, where we may expect the most developed structures in the short range forecast errors due to advection from data-sparse areas, were actually utilized. Jørgensen stratified the data subjectively according to flow type. For situations characterized by cyclonic south-westerly

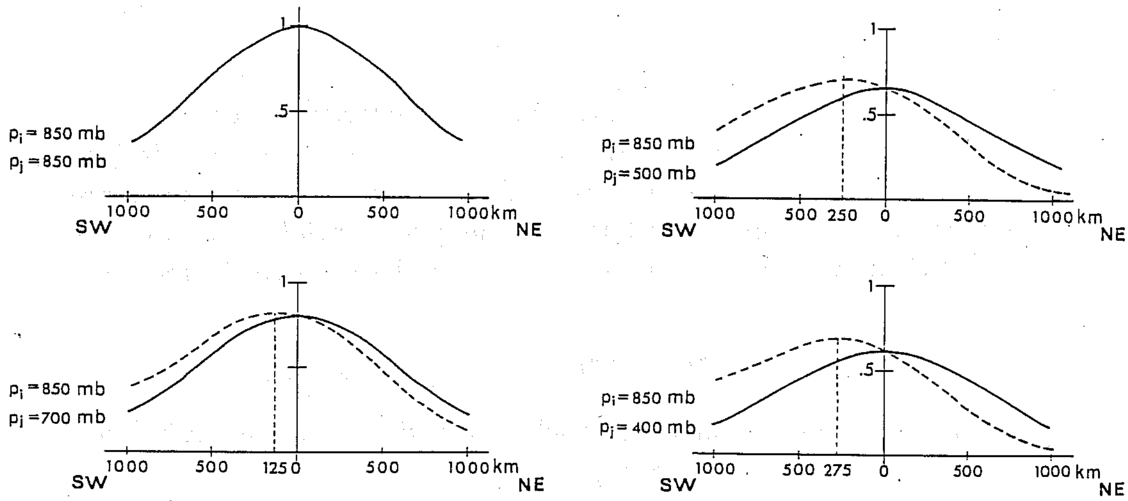

Figure 2: Vertical cross-sections southwest-northwest of structure functions. Full lines=without vertical tilt.Dashed lines=with vertical tilt.

flow, Jørgensen managed to find a significant baroclinic pattern in the forecast error correlations. The correlation maxima were tilting towards south-west for levels above a certain reference point and towards northeast for levels below. Jørgensen used Fourier-Bessel series to model the correlation functions. No assumption on horisontal/vertical separability was necessary to derive this correlation model. A cross-section of the derived correlation model is given in figure 2, illustrating southwesterly tilt of the correlation maxima. Jørgensen utilized the derived correlation model in data assimilation experiments, whereby she subjectively selected the area to utilize the tilt and the direction of the tilt. A minor positive impact of the tilting structure functions was noticed in a test case with a fast developing cyclone, initially being situated over the Eastern Atlantic and the British Isles. Jørgensen concludes that more development work is needed before the tilting structure functions can be used operationally, especially it is necessary to develop objective methods to determine when tilts in the structure functions should be applied and if so, in what areas and in what directions.

4 Review of analysis methods used for mesoscale case studies, nowcasting and very short-range forecasting

4.1 Successive correction schemes

Successive correction analysis schemes [6] have been widely applied in connection with diagnostic case studies, mainly since they are easy to apply. By successive iterations the analysis is modified , generally for smaller and smaller scales for each iteration. Formally one iteration is carried out as follows:

$$f_g(\lambda+1) = f_g(\lambda) + \frac{\sum_{i=1}^{N} W_{gi}^{\lambda}(f_i^{OBS} - f_i(\lambda))}{\sum_{i=1}^{N} W_{gi}^{\lambda}}$$

Here λ denotes the iteration number, f_g field (analysis or first guess) values, f_i field values interpolated to observation points, f^{OBS} observed values and W_{gi}^{λ} the interpolation weights. These weights may vary from iteration to iteration. Different versions of successive corrections mainly differ in the formulation of the weights. The Cressman SC method [12] has been frequently used in numerical weather prediction and it uses the following form of the weighting function

$$W_{gi}^{\lambda} = (R_{\lambda}^2 - r_{gi}^2)/(R_{\lambda}^2 + r_{gi}^2)$$

where r_{gi} denotes the distance between the gridpoint and the observation site. R_{λ} is an influence radius which is decreased for each iteration, resulting in corrections of smaller and smaller scales of the first guess field errors. It is also common to apply a spatial smoothing of the field between each iteration of the Cressman SC scheme.

The Barnes SC method, [3] and [4], has received wide acceptance for mesoscale analysis. It utilizes an exponential weighting function

$$W_{gi}^{\lambda} = \exp(-r_{gi}/K_{\lambda})$$

and it is normally applied in two scans, one weighted average scan and one weighted correction scan. The scan-dependent parameter K_{λ} is determined by specification of the desired spectral response of the analysis.

4.2 Statistical interpolation schemes

Albeit popular in numerical weather prediction, optimum (statistical) interpolation [14] has so far not been widely applied in other meteorological fields, probably because of the requirement to specify spatial correlation functions for the parameters to be analysed. Cats [11] utilized statistical interpolation in connection with an air pollution study to analyse wind components close to surface from a meso-scale network of stations. Within the Swedish project PROMIS for nowcasting and very short-range forecasting, various statistical interpolation schemes [1] have been developed mainly for analysis of near-surface parameters in a meso-scale grid (Δs=20km). Within these schemes, an-isotropy with regards to land-sea contrasts near the surface is handled by an-isotropic struture functions. The structure functions are separated into two parts, one taking care of the land-sea contrasts and one being a function of distance. The land-sea contrast is handled by classifying all stations and gridpoints according to their position in relation to the coastline. Thus the total correlation between the temperatures T_i in position "i" and T_j in position "j" is given by

$$\mu(T_i, T_j) = \beta(Class_i, Class_j)\alpha(r_{ij})$$

where $\alpha(r_{ij})$ is a distance-dependent function and the β-function is given by a table, see Table 2.

	Inland	Near coast	Coast	Inland lake	Sea
Inland	1.00	0.95	0.88	0.88	0.80
Near coast		1.00	0.95	0.95	0.88
Coast			1.00	0.95	0.95
Inland lake				1.00	0.95
Sea					1.00

Table 2: Correlation table used in a spatial correlation model for analysis of 2 met temperature to distinguish the positions of gridpoints and observation stations in relation to the coastline

4.3 Variational techniques

The concept of variational objective analysis was introduced by Sasaki [32]. Early applications utilized variational methods to combine univariately analysed wind- and mass-fields under the constraint of simple , e.g. geostrophic, relations. The main advantage of variational objective analysis, however, is the possibility to include more complex, also non-linear, constraints. Several authors have applied such variational analysis techniques also for meso-scale studies, e.g. Lewis and Bloom [22]. Recently McGinley [27] applied a three dimensional variational analysis scheme to ALPEX data to study some cases of interesting cyclogenesis with suspected meso-scale forcing. Starting from univariately analysed mass- and wind-fields, McGinley utilized the variational least-square minimization principle to modify these analysis values under a weak constraint of the full momentum equations (to minimize the deviations between observed and computed momentum tendencies) and under a strong constraint of conservation of mass. By including the lower boundary condition of full orographic blocking of the flow, finally, it was possible to obtain a very realistic analysis/diagnosis of the low-level wind field in the vicinity of the complex orographies of the Alps and the Pyrenees. In addition, features like frontal zones and vertical velocity patterns were much improved compared to the same features in the un-adjusted grid-point data.

Variational objective analysis schemes discussed above have required the input data on a regular grid in order to solve the variational equations. These gridpoint data were generally obtained by some simple spatial interpolation technique, e.g. successive corrections. Wahba and Wendelberger [37] have applied a variational analysis technique based on representation of the spatial variations with spline functions, minimization of the differences between analysis and observations directly in the observation points and utilization of generalized cross-validation to determine the proper smoothing of the field. The following function is minimized:

$$1/N\sum_{i=1}^{N}(f_i - f_i^{OBS})^2\sigma_i^{-2} + \lambda_{CGV}\int\int\sum_{j=0}^{m}(\frac{\partial^m f}{\partial x^m \partial y^{m-j}})^2 dxdy$$

Here "f" denotes the analysis field, "f_i^{OBS}" the observations, σ_i normalization factors to take observational accuracy into account, m a free parameter which is related to the desired power spectra of the analysis and λ_{CGV} the cross-validation parameter which determines the general fit of the analysis to the observed data (or the smoothness of the analysis). The cross-validation parameter is determined from the data by excluding, in principle, one observed datum at a time and determination of the parameter which in the mean gives the best fit to the excluded data.

Four-dimesional data assimilations methods, described in companion papers in this volume, are certainly most promising methods to be used for meso-scale case studies, especially since the relative lack of observed data on the meso-scale necessitates the use of full forecast model equations to compensate for the relative sparseness of data.

4.4 Analysis on isentropic surfaces

In order to utilize the full vertical resolution of radiosonde data, several investigators (Bleck[9] and Shapiro[34]) have used potential temperature as the vertical coordinate for objective analysis with meso-scale applications. Using this vertical coordinate system, features like fronts and jet-streams are represented in a more adequate manner. Reimer[31] has used a univariate isentropic statistical interpolation scheme for analysis of ALPEX data with ECMWF analysis fields used as first guess fields. An isentropic analysis system is developed within the framework of PROFS, the NOAA project for nowcasting and very short-range forecasting (see Benjamin[5]).

4.5 Comparisions of different methods

Seaman and Hutchinson [33] have carried out an extensive evaluation and comparison of various analysis methods for univariate analysis of a single parameter with a climatological mean value used as a first guess. 20 years of surface pressure data from 47 southeast Austalian stations were utilized for this test. 5 years of data were used to optimize the various parameters of the methods selected for comparison and the remaining 15 years of data were used for analysis experiments. Several different data densities were simulated by using only subsets of the stations. In order to do a proper verification of the analysis quality, data from some stations were with-held from the analysis and used for verification. Seaman and Hutchinson summarize their results as follows. Best results were obtained using statistical interpolation with structure functions having proper spectral properties. The Cressman SC method ranked only slightly below the best optimum interpolation schemes. Spline fitting techniques utilizing generalized cross-validation showed a greater sensitivity than most other methods to data density and to interpolation versus extrapolation. Methods that perfomed well in interpolation also detoriated less in extrapolation. Experiments with statistical interpolation combined with generalized cross validation to determine the signal-to-noise ratio indicated improved results when the covariances of obsevational errors or background errors were poorly known (e.g. approximated by a Gaussian function).

The application of scalar interpolation techniques, such as successive corrections, to the analysis of wind components involves a certain danger since a purely isotropic analysis, component by component, indirectly assumes that the variance of the divergent part of the wind field is the same as the variance of the rotational part of the wind field (Lorenc [25]). Pedder[30] has shown that this can lead to very erroneous analysis results in case the partition of the two parts of the wind field is not as implicitely assumed.

5 Experiences of high resolution analysis obtained during the HIRLAM project

The weather services of the Nordic countries and the Netherlands have established a common research project for the development of a HIgh Resolution Limited Area Model (HIRLAM) including a data assimilation system. Some experiences from the development of a data assimilation scheme for HIRLAM are reviewed below.

5.1 Sensitivity of analyses and forecasts with regard to analysis first guess error standard-deviations

During the first phase of the HIRLAM-project, several existing LAM systems were upgraded to meet the required horisontal resolution for HIRLAM ($\Delta s = 50km$) and used for experiments, see [15] and [28]. Here a sensitivity experiment with regard to forecast error standard-deviations used in the statistical interpolation scheme will be discussed. This experiment was carried out with the SMHI analysis scheme [1], a non-linear normal mode initialization scheme [8] and a limited area version of the ECMWF gridpoint forecast model [35].

A rapid small-scale cyclone development occured over the North Sea during the late evening of September 5 1985. At OO UTC September 6 1985, the cyclone was fully developed and situated over the Sea of Kattegat (Figure 3). This storm was not particularely well forecasted by any operational forecasting centre.

The trial +24h forecasts from 5 September 00 UTC carried out by several of the HIRLAM baseline systems managed to simulate this rapid cyclone development over the North Sea rather well, Figure 4 shows the forecast produced by the system described above.

In one sensitivity experiment the assumed forecast error standard deviations used in the analysis were modified to represent more updated values ([17] and [23]). The modified values were made a factor 0.4 smaller than the original values. This factor reflects the quality of ECMWF short range forecast errors compared to the quality of quasi-geostrophic SMHI forecasts of the 1970's. When the modified forecast error standard deviations were used for the analysis in data assimilation for 1 day, however, the prediction of the intensive cyclone development was far from being as good as with the analysis based on the larger forecast error standard deviations. The forecast based on the modified values was less intense and the position of the low over Kattegatt was also less well predicted (Figure 5). By tracing the forecast differences back to the initial state, it was possible to identify the main reasons for these differences to

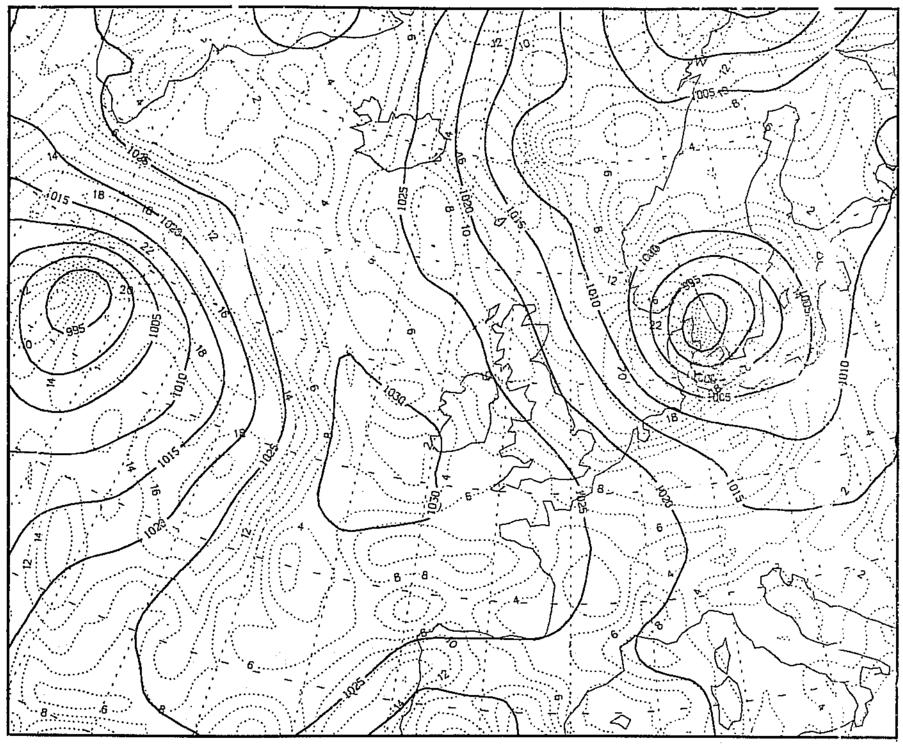

Figure 3: HIRLAM sea-level pressure analysis. 6 September 1985 00UTC.

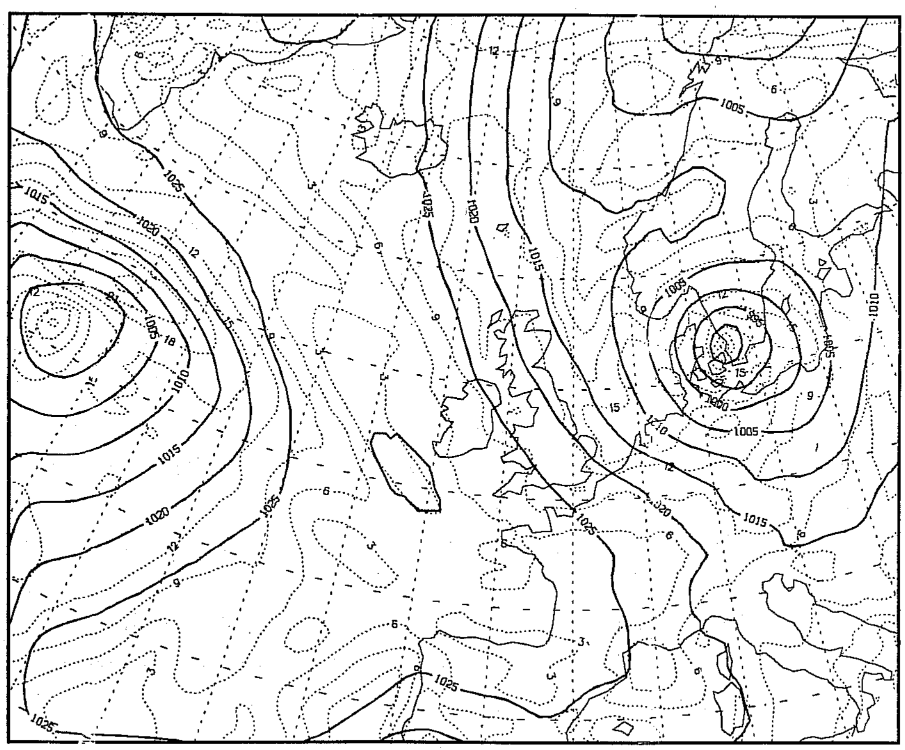

Figure 4: HIRLAM sea-level pressure forecast. 5 September 1985 00UTC +24 h. Initial analysis based on original SMHI forecast error standard deviations.

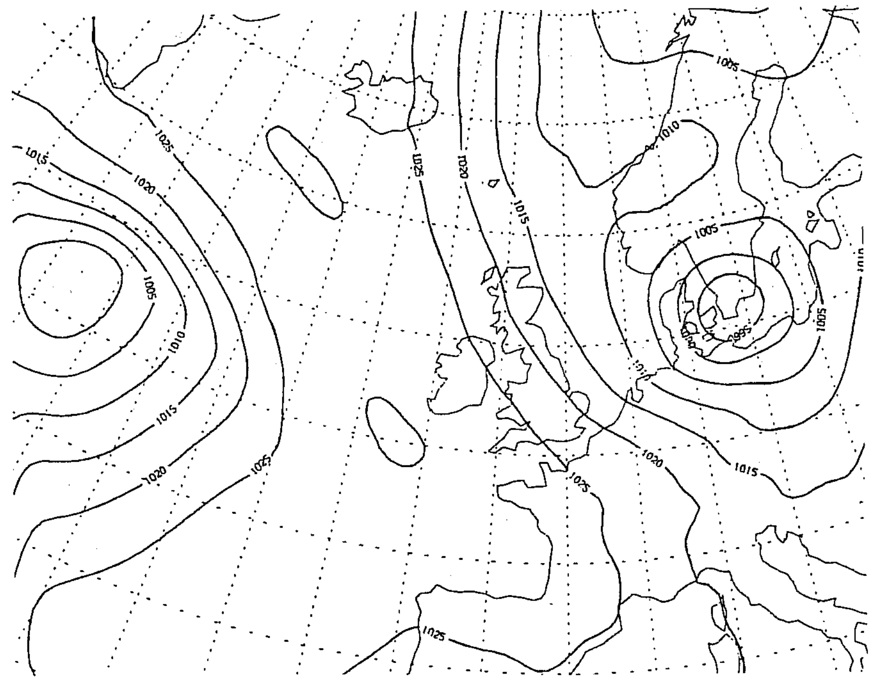

Figure 5: HIRLAM sea-level pressure forecast. 5 September 1985 00UTC +24 h. Initial analysis based on SMHI forecast error standard deviations multiplied by 0.4

be associated with the analysis of radiosonde data in the northern part of the British Isles. These radiosonde reports indicated a rather strong vertical wind shear, which was analyzed well when the larger forecast error standard deviations were utilized. However, when the smaller forecast error standard deviations were used, the analysis tended to believe more in the analysis forecast first guess field and the observed vertical wind shear was not fully drawn for by the analysis. Obviously the rapid cyclone development over the North Sea was very sensitive to the initial vertical wind shear - sensitivity studies with increased vertical diffusion of momentum in the forecast model also confirmed this hypothesis.

The results of this sensitivity experiment illustrate a general and serious weakness of present operational analysis schemes. The forecast error statistics have been accumulated from long series of forecast events, and these statistical parameters might not be the best ones for the analysis of a particular case.

Concerning the forecast error standard deviations, or rather the ratio between the forecast error standard-deviations and observational error standard deviations which express the "signal-to-noise" ratio of the observed values, Wahba [38] has suggested that generalized cross-validation can be used to determine this parameter from the observations themselves. In order to test the feasibility of the cross validation approach for the particular case studied, analysis values for each reporting position were determined without influence of the observed value for that position and for a range of signal-to-noise ratios. Table 3 includes RMS-differences between observed and interpolated sea-level pressure and pressure level geopotential values determined by the analysis scheme and with different factors multiplying the standard analysis forecast first guess errors used in the SMHI analysis scheme. It is of interest to see that the minimum values of these RMS-values are obtained for multiplication factors in between the standard and the revised values, indicating that for this particular case there is more information in the observed values than expected from the statistics as given by the ECMWF values.

Multiplication factor	500 hPa geopotential	Sea level pressure
0.4	1.167	1.193
0.5	1.065	1.094
0.6	0.999	1.018
0.7	0.981	0.985
0.8	0.981	0.975
0.9	0.994	0.978
1.0	1.018	0.990
1.1	1.050	1.008
1.2	1.083	1.030

Table 3: Normalized RMS-differences between observed and interpolated sea-level pressure and radiosonde geopotential observations for different forecast error standard deviations

5.2 Selection of an analysis scheme for HIRLAM

Taking the short project period, 3 years, for HIRLAM into account it was decided to develop a traditional intermittent data assimilation scheme based on optimum interpolation and non-linear normal mode initialization. Three different analysis algorithms, all related to optimum interpolation, were selected for further evaluation. One of the candidates, the serial approach suggested by Parrish and Cohn [29], was excluded on an early stage due to its huge requirements on core space for storage of covariance matrices and due to the difficulties to apply quality control within the scheme. The main reason for considering the serial approach was the possibility to utilize late arriving observations. The two remaining candidate algorithms are still being tested and evaluated. A limited area version of the ECMWF scheme has been selected for the "official" HIRLAM Level 1 system, while the Bratseth successive correction scheme is being tested within the Norwegian (HIRLAM Baseline) system. Main arguments for choosing the ECMWF scheme were its well-developed status, its continuous improvement by the ECMWF staff, its flexibility with regards to new data sources and the sound quality control. Main arguments for the Bratseth scheme were low computation cost and the possibility to avoid data selection.

5.3 Sensitivity of analyses and forecasts to correlation scale length and data search radius

The tuning of the ECMWF analysis scheme for the HIRLAM purposes was carried out by the aid of experiments, since no data base was available for modelling of forecast error statistics. Data assimilation sensitivity experiments were carried out with respect to variations in the analysis structure functions and data selection parameters [16]. The case with a fast developing cyclone over the North Sea, as described above, was used for these sensitivity studies.

The horisontal correlation of forecast first guess errors is given by a series of zero order Bessel functions in the ECMWF analysis scheme:

$$\mu(r) = \sum_{i=1}^{n} A_i J_0(K_i^0 r/R)$$

Here r denotes distance, n denotes the number of terms in the Bessel function series, K_i^0 denote the zeroes of the first order Bessel functions and R is a distance scaling factor (= 3000 km in the ECMWF original scheme). The A_i-coefficients, derived by regression from empirical correlations, were obtained from ECMWF ([17] and [23]).

Sensitivity tests were carried out by changing the number of Bessel terms (added terms representing smaller scales), by a simple change of the distance scaling factor R, by varying the maximum search distance for selection of influencing observations and by changing the assumed forecast error standard-deviations. The forecast error standard deviations are specified by the length of the time-period for the forecast errors to increase to the climatic ones.

Several sensitivity experiments with different values of these analysis parameters were carried out. In each case data assimilation for one day in advance of the initial forecast time, 5 September 1985 00UTC, was done. Here we will describe the results of a few of these experiments. We will limit our discussion to the effects on the initial wind shear analysis in the area of initial development over and west of the British Isles and on the effects on the +24 hour sea-level pressure forecast. A verification map for this forecast is given in Figure 3.

Figure 6 and Figure 7 contain maps from an experiment with 6 terms in the Bessel function series, with R reduced from 3000 km to 2250 km, with a data search radius of 930 km and with a time-period of 36 h for the forecast errors to reach the climatic ones. The vertical wind shear analysis shows up a smooth elongated structure west of the British Isles and the +24 h sea-level pressure forecast is an excellent one, better than those produced with the Baseline systems (Figure 4).

Figure 8 and Figure 9 contain maps from an experiment with R reduced further to 1500 km and with the data search radius reduced correspondingly to 540 km. Now the vertical wind shear map shows a more splitted pattern and with stronger vertical wind shears locally. Indeed there are no independent observations available to confirm which one of the vertical wind shear analyses is the best one over tha data sparse eastern Atlantic area. The impact on the forecasts shows that that the smaller scale initial analysis in the second experiment degrades the forecast quality. There is a less intensive development of the low pressure system and there is also an increased phase error. We may conclude that the simple reduction of the distance scaling factor R to 1500 km deforms the total assumed spectrum of forecast errors too drastically. Also for high resolution analysis there will be large scale forecast errors present which need proper treatment. Some further experiments showed that the specification of the proper spectrum as well as the proper data search radius were needed to analyze these larger scales.

A third experiment with R kept at its ECMWF value (3000 km), with 9 terms in the Bessel function series instead of 6, with a data search radius of 930 km data and other parameters being the same as in the experiments described above, was also carried out. The forecast quality was as excellent as for the first experiment described above.

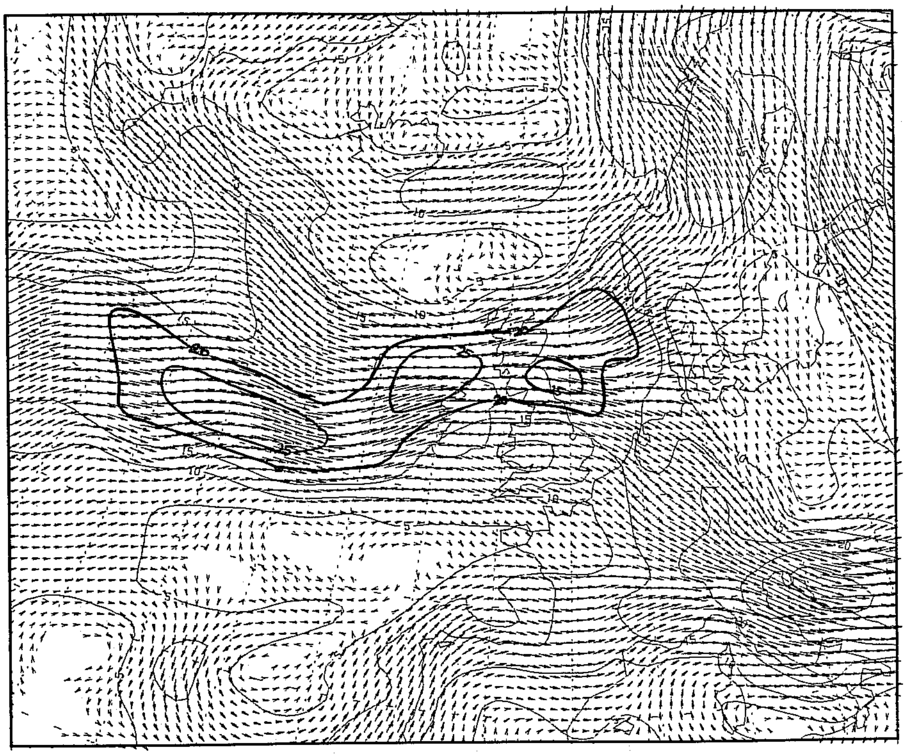

Figure 6: HIRLAM 850/500 hPa vertical wind shear analysis. 5 September 1985 00UTC. n=6, R=2250 km, Data search radius=930 km (see text).

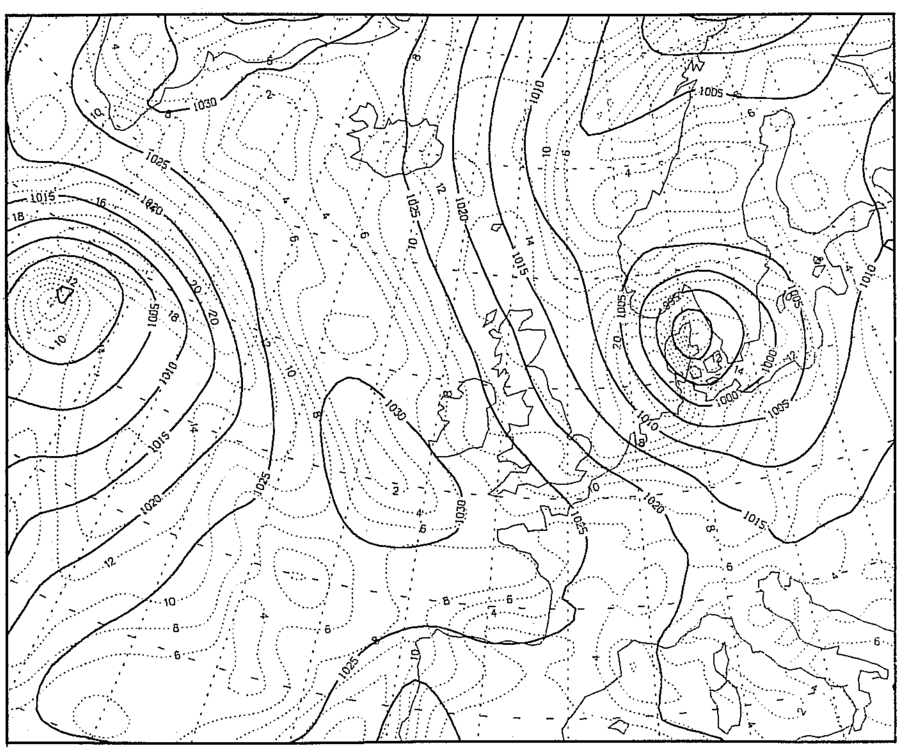

Figure 7: HIRLAM sea level pressure forecast. 5 September 1985 00UTC +24 h. n=6, R=2250 km, Data search radius=930 km (see text).

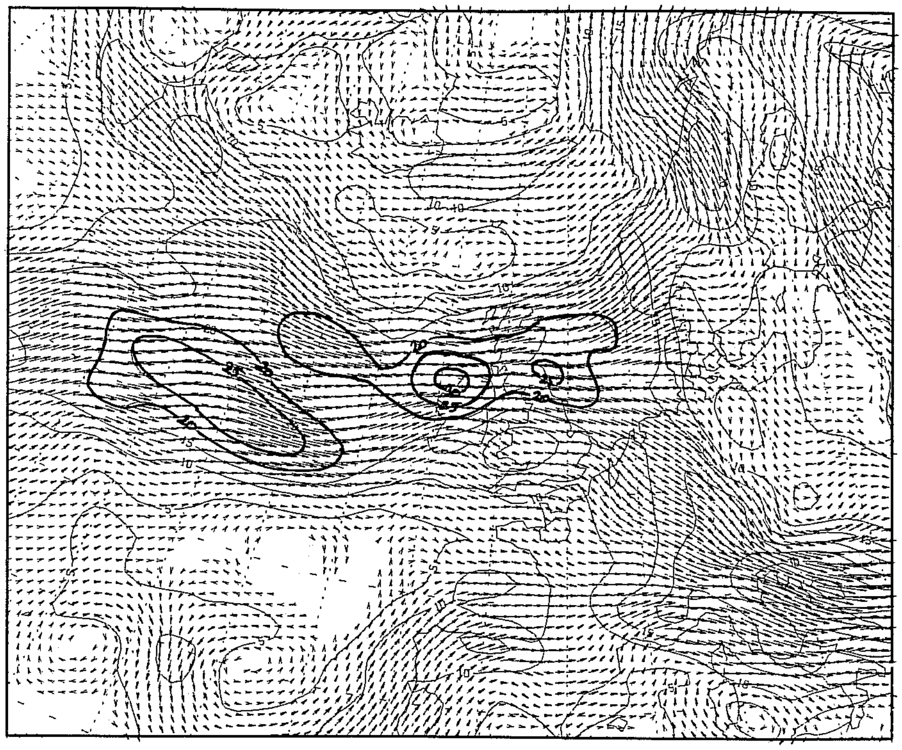

Figure 8: HIRLAM 850/500 hPa vertical wind shear analysis. 5 September 1985 00UTC. n=6, R=1500 km, Data search radius=540 km (see text).

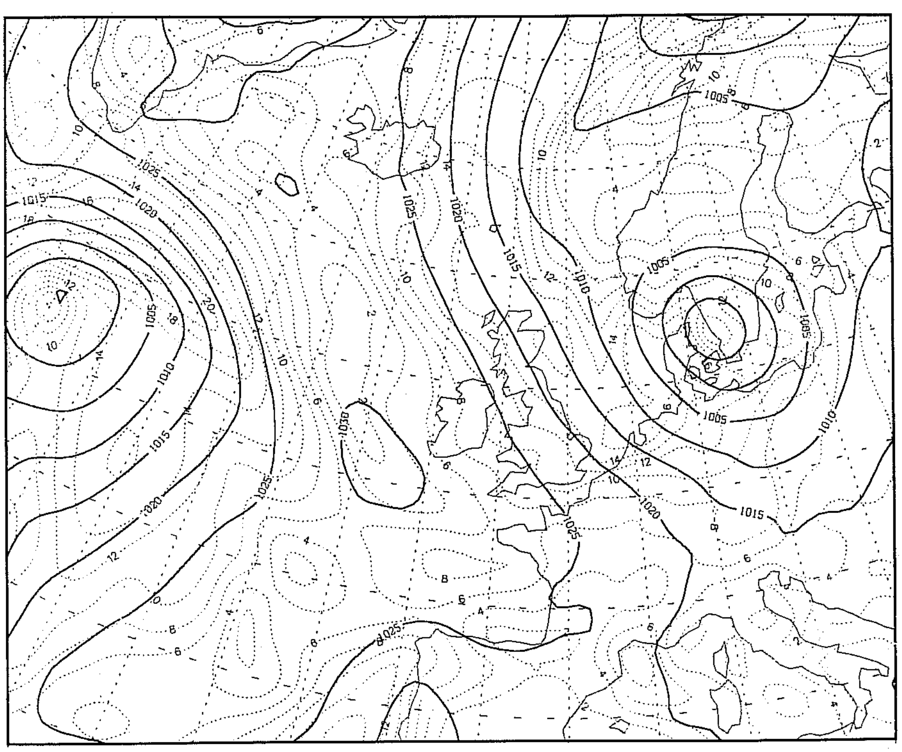

Figure 9: HIRLAM sea level pressure forecast. 5 September 1985 00UTC +24 h. n=6, R=1500 km, Data search radius=540 km (see text).

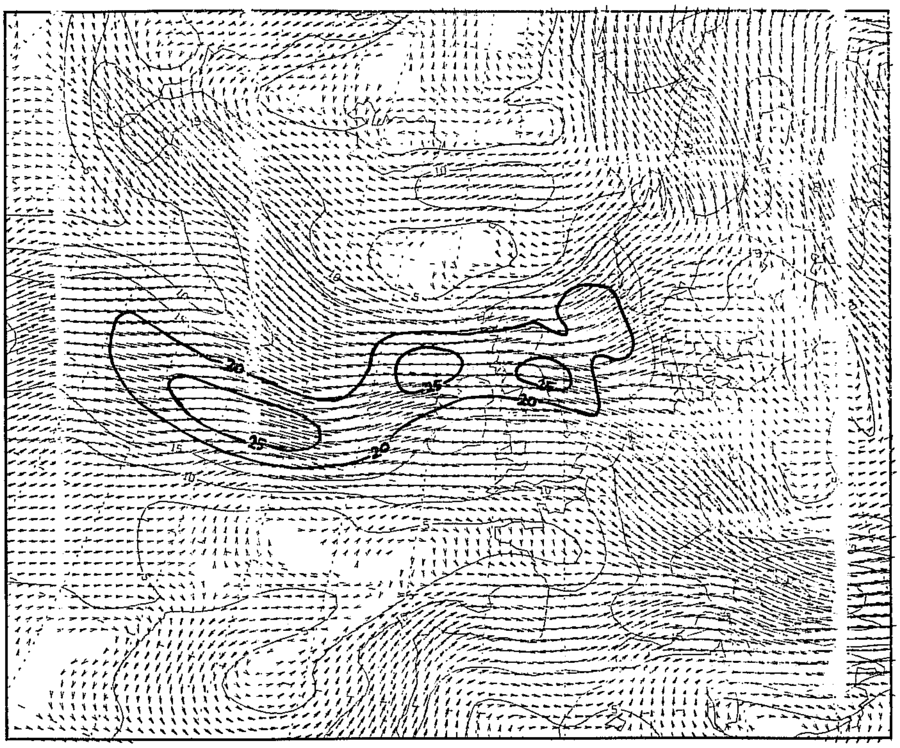

Figure 10: HIRLAM 850/500 hPa vertical wind shear analysis. 5 September 1985 00UTC. n=9, R=3000 km, Data search radius=930 km (see text).

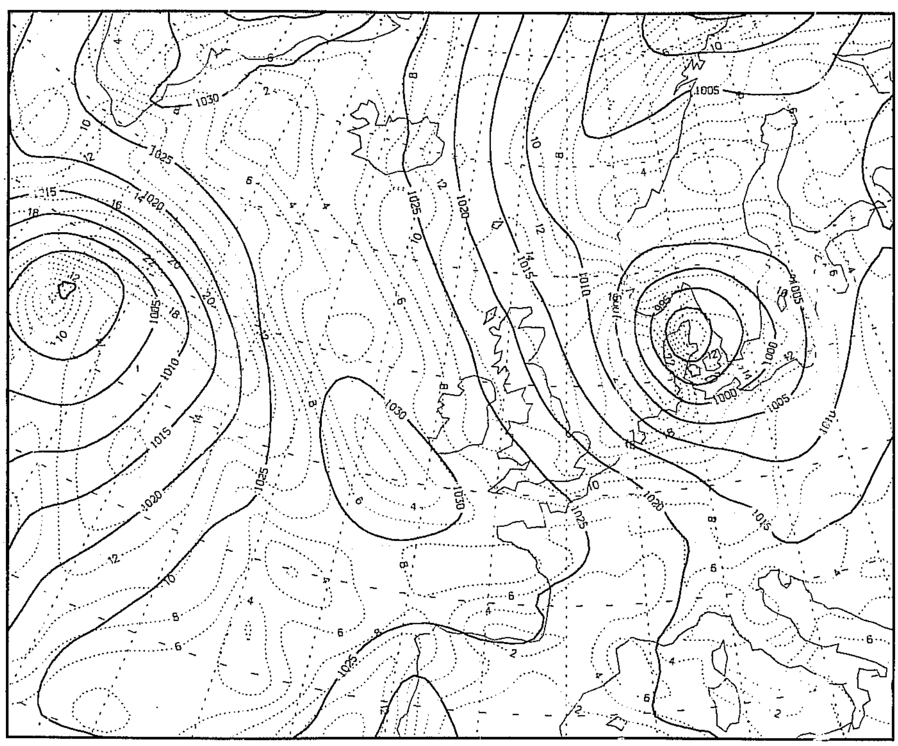

Figure 11: HIRLAM sea level pressure forecast. 5 September 1985 00UTC +24 h. n=9, R=3000km, Data search radius=930 km (see text).

6 Concluding remarks

Methods for high resolution objective analysis were reviewed and discussed. Issues as the broad spectrum of scales, an-isotropies and non-stationarity were identified as important problems when we go towards higher resolution analysis. Flow-dependent structure functions and four-dimensional data assimilation techniques were mentioned as measures to handle these problems. A clear preference for the four-dimensional data assimilation approach, being based on physics and dynamics and being more flexible than statistically determined structure functions, was expressed.

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