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Use of conventional surface observations in three dimensional variational assimilation

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ABSTRACT

Variational analysis schemes are capable of using the observed quantities directly rather than first converting the observations to the quantities of the model. The model variables are used to construct, by means of so called 'observation operators', equivalents of the observed data, enabling the comparison between model and observation to take place in terms of the observed quantity. In this paper we assimilate SYNOP, SHIP and DRIBU observations of two-metre temperature and ten-metre wind using a three-dimensional variational analysis scheme (3D-Var), with non-linear observation operators which depend on the model variables at the lowest model level and at the surface. The surface observation operators are related to the physical processes of the surface layer based on Monin-Obukhov similarity theory. They match the physical parametrization used in the model surface layer.

The variational analysis minimizes a cost-function consisting of three terms which respectively measure: 1) the "distance" of the analysis field to the observations; 2) the "distance" to the background (a 6-hour forecast) and 3) the amount of gravity wave activity in the analysis. Surface fields are currently not part of the control variable, which means that they are not allowed to change during the minimisation. We show that this restriction makes it difficult to use two-metre temperature data over land. The 3D-Var method is nonetheless more general than the operational Optimum Interpolation scheme. The adjoint technique enables a consistent treatment of the non-linear and multi-variate aspects of the observation operators. We show that the 'analysis weight' of the data is modulated by the near-surface stratification and by the surface roughness. Regarding the multi-variate aspects we show that wind data have only a small impact on the analysed low-level temperature, whereas temperature data over land can have a strong influence on the analysed wind field.

Assimilation experiments over five days, with and without the surface data, have been compared and verified against ERS-1 (European Remote Sensing satellite) scatterometer winds. The observations have a positive impact on the analyses over sea, improving the wind and geopotential fields at the surface and in the lower troposphere. The forecast impact is, in these experiments, positive in the very short range, becoming slightly negative after 24 hours. The reason for the slightly disappointing forecast impact is likely to be related to deficiencies in the background term of the variational analysis, at the time of these experiments.

1. INTRODUCTION

We define as *conventional* surface observations all the ground based information coming from surface stations over land: SYNOP, and over sea: SHIP and DRIBU (drifting buoys). SYNOP are synoptic surface observations, either manual or automatic, from a level site. Surface pressure, 10 m wind components, 2 m temperature and 2 m dew-point temperature are observed at a majority of meteorological stations, and made globally available on a six-hourly basis. The total number of such observations available during a 6-hour time period is between three and five thousand (not counting multiple reports from the same station), mainly in the Northern Hemisphere. The large number, and the good areal coverage of such observations make them potentially useful in data assimilation and numerical weather prediction (NWP). In this paper, we investigate the impact of surface temperature and wind data in NWP, when assimilated through a three-dimensional variational analysis scheme.

Modern multi-variate data assimilation schemes simultaneously use observations of temperature, height, wind and surface pressure to create a consistent three-dimensional set of analysed fields of wind and mass (temperature and surface pressure) (e.g. *Lorenc*, 1981) to use as initial data for numerical weather forecasts. The surface wind data improve the analysis of near-surface pressure gradients and help define the position of cyclones in the mid-latitudes, in addition to their direct impact on the low-level wind analysis itself. Surface wind data are also important for the analysis of tropical disturbances (*Reed et al*, 1986) and lower tropospheric divergence in the Tropics (*Undén*, 1989). The near-surface temperature data are, for the purpose of NWP, generally less important than the wind data due to their stronger temporal and spatial variability, and their weaker link to the synoptic-scale dynamics of the atmosphere. The process of data assimilation filters the data to the scales represented by the forecast model (*Hollingsworth*, 1987). In some air pollution studies it is also advantageous to use analysed fields rather than using the near-surface observations directly: the analysed fields give wind speed values more representative for the grid scale and more suitable for calculation of stability parameters (*Meuller et al*, 1990). Two-metre temperature (and relative humidity) observations have also been used to infer a realistic soil moisture content and soil temperature for use in NWP (*Mahfouf*, 1991; *Bouttier et al*, 1993). However, a realistic land surface parametrization is necessary for such an analysis scheme.

A global variational data assimilation scheme is currently being developed at ECMWF (*Pailleux et al*, 1991; *Heckley et al*, 1992; *Vasiljević et al*, 1992; *Courtier et al*, 1993; *Andersson et al*, 1994a; 1994b). The three-dimensional version of the variational scheme (3D-Var) is due to replace the operational Optimum Interpolation (OI) scheme in the near future. The variational scheme uses all available observations in one go. It performs a global, iterative minimisation of the 'distance' between the analysis and the observations, while remaining 'close' to the given background information (a 6-hour forecast) - whereas OI gives an approximate solution to the same analysis problem using a limited number of observations around a group of analysis grid points.

A common problem to all efforts to assimilate surface observations is how to spread the information correctly from the surface to the free atmosphere above (*Hoffman*, 1992), and extract from the observations a dynamically consistent impact which persists in both the assimilation and the forecast. In 3D-Var, as well as in OI, the extent to which the information is spread in the vertical is determined by the vertical correlations of the forecast error, sometimes called 'structure functions'. These are in neither scheme dependent on the synoptic situation, but reflect the average conditions of the atmosphere. It was observed by *Hoffman* that the upper-air analysis increments due to surface wind data (in his case ERS-1 scatterometer data) tend to decay during the 6-hour forecast of the assimilation cycles. This is an indication that it may be difficult to correct the most important, fast-growing errors in the initial data with the information from surface observations.

In a variational scheme, the comparison between model and observation takes place in terms of the observed quantity. Model equivalents of the observed quantities are calculated by applying a specific operator for each type of observation - the so called <u>observation operators</u> (*Pailleux et al*, 1991). The observation operators can be a function of any analysis variables as well as any other model variables, auxiliary parameters and constants. The analysis variables (or 'control variables') will be adjusted by the variational scheme such that the fit between model and data is improved. Other input variables to the observation operator will remain unchanged. In this paper we assimilate conventional surface observations (10 m wind and 2 m temperature) by observation operators which interpolate model variables between the lowest model level and the surface. The interpolation is based on the Monin-Obukhov similarity hypothesis. The observation operators are related to the physical processes of the surface layer and match the model's boundary layer parametrization, following *Geleyn* (1988).

The theoretical advantages of such operators (compared to linear observation operators) are that they depend on the model stability functions and take into account information regarding surface processes such as friction. The adjoint technique enables a consistent treatment of the non-linear and multi-variate aspects, whereby surface wind data affect not only the analysis of the wind field but also the analysis of temperature, through the stability dependency of the observation operator. Surface temperature data may similarly affect the wind analysis. The possibility of using, in a consistent way, data which are linked to the model variable through a (weakly) non-linear operator is one of the major advantages of the variational analysis (*Pailleux et al*, 1991).

The current operational use of these data in the ECMWF OI scheme (*Lorenc*, 1981) is an approximation of the 3D-Var method. In OI, the difference between the observations and the first guess is calculated using the full observation operator, and in the analysis it is simply assigned to the reported pressure. The interpolation to the lowest model level then depends on the vertical structure functions, implying a linear relationship between the data and the analysed quantity on the lowest model level (at approximately 30 m) for the increments. The SSI (spectral statistical-interpolation) scheme at NMC (*Parrish and Derber*, 1992), assigns the observation departure from the first guess directly to the lowest model level, implying a one-to-one correspondence between the observed and the analysed quantity, for the increments. This simplification is not necessary in 3D-Var.

The OI (and SSI) approximations also mean that no information about variables other than the observed one is transferred to the analysis, i.e. these schemes are uni-variate with respect to the surface data. The multi-variate and non-linear aspects of 3D-Var have proved to be important with respect to satellite data, e.g. TOVS (*Andersson et al*, 1994a) and scatterometer (*Stoffelen et al*, 1993). In this paper we investigate whether it is important also in the case of conventional ground based observations.

We perform assimilation experiments over a five day period (at spectral truncation T106) with and without the surface wind and temperature data, in order to compare the quality of the analyses and of forecasts run from the two sets of analyses. We also compare the variational analyses with operational OI analyses at resolution T213. The scatterometer instrument of the ERS-1 (European Remote Sensing) satellite provides reliable and independent data of near-surface wind against which analyses can be validated (*Stoffelen et al*, 1992). In our study ERS-1 data have been used to verify the position of fronts and low pressure systems in the two analysis experiments.

In section 2, the three-dimensional incremental variational analysis scheme is briefly described. Section 3 contains the principles on which the surface observation operator is based - the mathematical details have been given in an earlier paper by *Vasiljević et al* (1992). Simplified experiments in section 4 illustrate some important properties of the observation operator for 2 m temperature and 10 m wind. The impact of surface observations on analyses and forecasts is presented in section 5. Finally, concluding remarks and a summary are given in section 6.

2. THE VARIATIONAL SCHEME

The variational analysis scheme at ECMWF is currently under continuous development. This section briefly outlines the scheme as used in these experiments.

2.1 General formulation

The variational analysis seeks to minimize a cost function $J(x)$ with respect to the control variable x, which is a representation of the atmospheric state (*Talagrand*, 1988). The cost function consists of three terms which measure the degree of mis-fit of x to the observations (J_o), to the background field (J_b) and to the slow manifold (J_c).

$$J(x) = J_o + J_b + J_c \tag{2.1}$$

$$J_o = (H(x) - y)^T O^{-1} (H(x) - y) \tag{2.2}$$

$$J_b = (x - x_b)^T B^{-1} (x - x_b) \tag{2.3}$$

$$J_c = \alpha_g \left| \frac{dG}{dt} \right| \tag{2.4}$$

where x_b represents the background field (typically a 6-hour forecast, sometimes called 'first-guess') with the forecast error covariance matrix B. y is the observation vector and O is the covariance matrix of observation errors, containing both measurement and representativeness errors (*Lorenc*, 1986). H is the ensemble of operators (linear and/or non-linear) transforming the control variable x into the equivalent of each observed quantity. We will call H the 'observation operator', as in *Pailleux et al* (1991). The J_c-term measures the gravity wave tendency with an energy norm (*Thépaut and Courtier*, 1991), with α_g a tuning parameter. It can be shown that for a linear operator H, without a J_c-term, the variational analysis is equivalent to the OI analysis (*Lorenc*, 1986).

To reduce the memory and computational cost of 3D-Var an alternative formulation has been described by *Courtier et al* (1994). Following their formulation the observation increments are computed at high resolution (typically triangular spectral truncation T106) and the minimisation is performed at a lower resolution (typically T63).

2.2 Mass/wind balance

The J_b part of the total cost function is defined as described by *Heckley et al* (1992) and *Courtier et al* (1993). Multivariate balance is imposed on the increments by J_b using Hough-mode separation and penalisation of the gravity modes, which provide a mass/wind coupling over the whole globe. It is assumed that 5% of the forecast error variance lies in the gravity wave part of the flow and 95% in the Rossby part. In the separation between Rossby and gravity waves all vertical modes are used. Horizontal modes used are those corresponding to vertical modes 1 through 7. Beyond vertical mode 7 the same set of horizontal modes are used for all higher modes. The control variable x consists of the mass-variable P, vorticity, divergence and specific humidity in spectral space. ($P = \Phi + RT_r \ln p_s$ where ϕ is a linearized form of geopotential height, T_r is the reference temperature =300 K, and p_s is surface pressure)

2.3 Structure functions

The specification of forecast error statistics assumes homogeneous and isotropic correlations with a horizontal variation of the forecast error variances (as in ECMWF OI, *ECMWF Research Manual No 1*), but in 3D-Var the formulation does not however assume separability between the vertical and horizontal directions. A fully 'non-separable' formulation is used (*Andersson et al*, 1994b) based on statistics derived by *Rabier and McNally* (1993) in a study of differences between 24 and 48 hour forecasts, valid at the same time, a technique proposed by *Parrish and Derber* (1992). The broadness of the vertical structure functions in 3D-Var depends on the horizontal scale, and the shape of the horizontal correlations depends on vertical level. The vertical correlations are generally sharper (broader) for smaller (larger) horizontal scales. The horizontal correlations are generally broader in the stratosphere than in the troposphere.

2.4 Minimisation

When J_o, J_b and J_c have been computed, the gradient of the cost function with respect to the control variable is found using the technique that relies on the adjoint of tangent-linear operators (*Kreyszig*, 1989). The control variable is updated after each iteration of the minimisation. The whole procedure is repeated until the gradient of the cost function is small enough or the maximum number of iterations has been reached. In our experiments we allowed a maximum of 50 iterations. The minimisation algorithm used (M1QN3, *Gilbert and Lemaréchal*, 1989) is based on the limited memory quasi-Newton method.

3. THE SURFACE OBSERVATION OPERATOR

In this section we describe the observation cost function and the surface observation operator used for assimilating 2 m temperature (T_{2m}) and 10 m wind components (u_{10m}, v_{10m}) from SYNOP, SHIP and DRIBU in 3D-Var.

We assume that the observation errors are uncorrelated between different observation points and between different observation types. In this way one can separate each observation's contribution to J_o (*Pailleux et al*, 1991). However, the assumption that observation errors are uncorrelated is not always correct because the observation errors contain the representativeness errors: in some weather conditions, closely-spaced surface observation errors can be correlated. This effect is omitted in our scheme.

When there is at least one model level within the boundary layer, observation operators (as introduced above) can be defined to compute model equivalents of the observed T_{2m}, u_{10m} and v_{10m}, by interpolation of meteorological variables between the lowest model level and the model surface, according to the surface parametrization processes of the forecast model (*Geleyn*, 1988). The model-based values ($H(x)$ in Eq 2.2) are functions of temperature T_l, specific humidity q_l and wind components u_l, v_l (subscript l indicating lowest model level) and surface pressure p_s. The observation operators are also dependent on surface variables, i.e. surface temperature T_s, roughness length z_0, vegetation C_v, soil wetness of the first model soil layer W_s, water content of the skin reservoir W_r and snow S_n. Formally we can write:

$$(u_{10m}{}^{pp},\ v_{10m}{}^{pp}) = H_1\,(T_l, q_l, u_l, v_l, p_s, T_s, z_o, C_v, W_s, W_r, S_n) \tag{3.1}$$

$$T_{2m}{}^{pp} = H_2\,(T_l, q_l, u_l, v_l, p_s, T_s, z_0, C_v, W_s, W_r, S_n) \tag{3.2}$$

The detailed mathematical description of the operator is given in *Vasiljević et al* (1992). We give here the general principles on which the method is based.

The interpolation operators H_1 and H_2 are based on the Monin-Obukhov similarity hypothesis, i.e. that the structure of the atmospheric surface layer depends only on the dimensionless distance to the ground $\zeta = (z-z_0)/L$, where L is the Obukhov length. It is possible to find exact solutions of (3.1) and (3.2), based on the integration of the observed Obukhov stability functions (see *Dyer*, 1974 and *Högström*, 1988 for a review of experimental results), but they are not useful for two reasons. Firstly, they involve the solution of a non-linear system of equations by iterative methods, in all but the neutral cases, which is expensive for implementation in an operational system. Secondly, there would be no guarantee that the solution will match the stability functions used by the numerical model providing the background field. In fact, the ECMWF model formulates the stability dependency in the boundary layer in terms of a bulk Richardson number (*Louis*, 1979), R_i:

$$R_i = \frac{g\,\Delta z\,\Delta\theta_v}{C_p\theta_v|u|^2} \tag{3.3}$$

where $\Delta\theta_v$ is the virtual potential temperature difference between the lowest model layer and the surface, u is the model wind speed, C_p is the specific heat, z is the height and g is the acceleration of gravity. The relation between the bulk Richardson number, used in the model surface layer, and the Obukhov length, mentioned above, is again non-linear.

As explained in *Geleyn* (1988) and *Vasiljević et al* (1992), it is possible to have an interpolation operator which obeys the following properties:

i) the operator is non-iterative;

ii) the stability functions implicitly used by the operator match closely the stability functions used by the model physics.

Following Geleyn (1988) our computation of H_1 and H_2 involves the following steps:

1) Compute the stability dependent exchange coefficients for heat (C_H) and momentum (C_M) between the surface and the lowest model level. This step reproduces the computations of the model physics.
2) Compute the virtual potential temperature and wind components at the observation height, using C_H, C_M, lowest model level wind components, virtual potential temperature and surface temperature. This step is mathematically equivalent to two integrations of the simplified stability functions (between the surface and the model level height, and between the surface and the observation height), followed by elimination of the Obukhov length between the two integrated formulae.

It is important to stress that using the above described operator is equivalent to assuming simplified analytical stability functions in the surface layer compatible with the exchange coefficients, hence compatible with the stability information and the fluxes assumed.

4. SOME PHYSICAL PROPERTIES OF THE OPERATOR H

We have seen from the two preceding sections that our observation operators are functions of the model variables at the lowest model level and of surface temperature and soil variables. In our implementation of 3D-Var only the model variables are varied in order to fit the observations - i.e. temperature (mass), wind and humidity at the lowest model level are adjusted. In 4.1 we study the implications of not allowing the surface variables to change during the minimisation.

The operators are also functions of the height above ground at which the observations have been made. The observation height is not always accurately known, especially for SHIP data. These observations may have been taken from the deck of the ship which can be 15 m or more from the ocean surface. In 4.2 we study the sensitivity of the temperature operator to a mis-specification of the observation height.

The non-linear and multi-variate aspects of the operators are studied in 4.3 and 4.4, respectively.

4.1 Sensitivity to surface variables

In order to study the sensitivity of the 2 m temperature operator to the surface variables, we performed an analysis experiment using no other observations than 2 m temperature data, over both sea and land.

4.1.1 *Surface temperature*

The most important contributor, among the surface variables, to the calculated T_{2m} is T_s, the surface temperature. Keeping T_s fix during the minimisation while varying T_l (the lowest model level temperature, at approximately 30 m above ground) will modify the temperature lapse rate of the surface layer. Scatter plots of this lapse rate ($T_l - T_s$) at the observation points *before* (abscissa) versus *after* the minimisation (ordinate), in other words first-guess versus analysis, show that this indeed happens. Fig 1 shows all data over land in a given 6-hour period and Fig 2 shows the data over sea. Over land (Fig 1), many points that were near-neutral initially become largely stable ($T_l - T_s > 0$) or largely unstable ($T_l - T_s < 0$) after the minimisation. These large changes in the lapse rate in cases which were near-neutral initially seem very unrealistic. It seems more likely that the model's T_s in reality has an error similar to T_l. Adjusting both would allow the lapse rate to be preserved. Over sea (Fig 2), the points cluster around the main diagonal, indicating that the changes to the near-surface stratification have been small.

Model surface variables are not included in the control variable of 3D-Var, which means that H_2 cannot be minimized with respect to T_s, W_s, W_r and S_n. Since T_s is not changing during the minimisation, the thermal stability [$\Delta\theta_v$ in (3.3)] is changing only because the lowest model level temperature has changed. As a consequence, the vertical temperature gradients in the surface layer is not controlled during the minimisation. A future simplified implementation may consist of keeping $\Delta\theta_v$ constant during the minimisation procedure (*Coiffier et al*, 1987).

Such problems do not occur for the assimilation of 10 m wind observations, because the wind boundary condition at the surface is zero, in all conditions of thermal stability.

Having a constant surface temperature in the minimisation is not a serious limitation over sea for the following reasons: i) due to its large thermal inertia, the ocean surface temperature adjusts slowly to the boundary layer forcing; and ii) the typical values of surface wind speed over sea are larger than land values, since the oceans have a smaller roughness length. The ocean surface layer is much more often in a state of near-neutrality than the land surface layer.

4.1.2 *Soil variables*

The soil water variables (W_s, W_r, S_n) enter in the observation operator only through the definition of an apparent humidity at the surface. The dependency of the operator on those variables can be neglected and they can be kept constant during the minimisation.

4.2 Observation height

The actual height at which SHIP observations have been made is not known from the reports. In the calculation of the model equivalent of the observations we assume, however, that the observation height is 2 m, also for SHIP data. The data could in reality correspond to a height of 15 m or more above the ocean surface. In order to study the significance of this discrepancy we carried out an experiment in which the calculations were performed with the observation height set to 15 m instead of 2 m, and we compared the result for all SHIP data. Fig 3 shows a scatter diagram of the difference between the two calculations $T_{2m}-T_{15m}$ versus the temperature lapse rate of the surface layer T_l-T_s. T_{2m} and T_{15m} are the model-based temperatures assuming the observation height at 2 m and at 15 m above the ocean surface, respectively.

Fig 3 suggests that the error in assuming 2 m instead of 15 m for the observation height is negligible in neutral conditions, $T_l-T_s=0$. It grows approximately linearly with the absolute value of T_l-T_s on both the stable and the unstable sides. For very unstable cases, e.g. $T_l-T_s=-4$ K there is a discrepancy of around 1 K, and similarly for stable cases. Strongly unstable cases seem to be more frequent, so cold air advection over warm sea is the typical situation in which the calculation is particularly sensitive to the assumed observation height. The observation height has to be defined correctly for accuracy of results in such conditions.

4.3 Non-linear aspects. Comparison with a simplified analysis method

The solution to the 3D-Var problem without J_c is

$$x - x_b = BH'^T\,(H'BH'^T + O)^{-1}\,(H(x) - y) \tag{4.1}$$

In the univariate, one-dimensional case, ignoring vertical correlations in B, we have

$$H'BH'^T = (H'\sigma_b)^2 = \sigma_s^2 \tag{4.2}$$

where σ_s^2 is the "effective" forecast error variance for the quantity observed, in our case T_{2m} and U_{10m}, and H' is $\frac{\partial H}{\partial T_l}$ and $\frac{\partial H}{\partial U_l}$, respectively, where l indicates lowest model level. If the observation operator is non-linear, H' is not constant. We see from (4.2) that variations in the magnitude of H' modulates the value of the effective forecast error for T_{2m} and U_{10m}, which means that the weight given to the observations depends on H'.

The value of H' can easily be computed from the gradient of the cost function available at the end of the adjoint computation. For a single observation we have

$$\frac{\partial J_o}{\partial x} = \frac{2}{\sigma_o^2}(H(x)-y)\frac{\partial H}{\partial x} \tag{4.3}$$

where σ_o is the observation error standard deviation. Normalizing, arbitrarily setting $H(x) - y = 1$ and $\sigma_o = 1$, we obtain

$$H' = \frac{\partial H}{\partial x} = \frac{1}{2}\frac{\partial J_o}{\partial x} \tag{4.4}$$

H' can now be interpreted as a correlation between the model quantity (at the lowest model level) and the observed quantity. Its value is thus less than or equal to one. Study of H' can help us understand the difference between 3D-Var and the simplified, linear analysis method used by e.g. NMC (National Meteorologic Centre, Washington) SSI (*Parrish and Derber*, 1992) and ECMWF OI (*Lorenc*, 1981). In the simplified method, the full operator is used to calculate the departure $H(x) - y$, and the departure is assigned directly to the lowest model level for the analysis (SSI) or to the reported pressure (OI). The analysis then sees the surface data as if they were lowest model level data, and is characterized by $H' = 1$ (In ECMWF OI the correlation in the B-matrix becomes slightly less than one if the reported pressure is different from the lowest model level pressure). Instead, using the full operator and its adjoint H' is less than one, indicating a more indirect link between the surface data and the analysed quantity. Consequently, σ_a is less than σ_b, which gives the effect of drawing less to the data.

Fig 4 shows H' as a function of the bulk Richardson number for each SYNOP and DRIBU within a 6-hour analysis period. Fig 4a shows the partial derivative of H with respect to T_l for T_{2m} observations while Fig 4b shows the partial derivative of H with respect to U_l for U_{10m} observations. Different symbols are associated with different roughness lengths, z_o, as indicated in the legend. In general the weight given to the data decreases with increased z_o.

We can see that for R_i negative (unstable stratification) and for small values of z_o, H' is close to one, which implies that the 'full' 3D-Var method and the 'simplified' analysis method give similar results in such cases, for both temperature and wind. In very stable cases ($R_i > 0.1$), on the other hand, H' is close to zero for temperature (Fig 4a), which means that hardly any information will be extracted from the T_{2m} data in such conditions. There is a gradual transition between these two extremes, in near-neutral condition, which could not be taken into account with the simplified method. For wind, $H' \approx 0.7$ in stable conditions (Fig 4b), which is equivalent to an increase in σ_b by a factor 1.4. There is more scatter in this diagram than for temperature, indicating that other factors than stratification and surface roughness are influencing the boundary layer wind profile, one of which could be the wind speed itself.

4.4 Multi-variate aspects

The adjoint technique applied to (3.1) and (3.2) gives non-zero gradients with respect to T_l, u_l, v_l (and q_l and p_s, which we ignore in the following), for both operators, H_1 and H_2. This implies that T_{2m} observations can provide information on the near-surface wind, and similarly that U_{10m} observations can provide information on the near-surface temperature. In order to test the importance of this multi-variate aspect we devised similar, but uni-variate, operators:

$$(u_{10m}{}^{pp}, v_{10m}{}^{pp}) = H_{S1}(.. T_{lb}, u_l, v_l, \ldots) \tag{4.5}$$

$$T_{2m}{}^{pp} = H_{S2}(\ldots T_l, u_{lb}, v_{lb}, \ldots) \tag{4.6}$$

where subscript b refers to background values, interpolated to the observation points.

Four global 3D-Var analyses were performed, using SYNOP and DRIBU data for 930816-12 UT: A) Only T_{2m} data, multi-variate operator; B) Only U_{10m} data, multi-variate operator; C) Like A, but uni-variate and D) Like B, but uni-variate. The J_b mass/wind coupling gives multi-variate analysis increments in all four experiments. In order to isolate the multi-variate effect of the observation operators, we study wind differences between experiments A and C, and temperature differences between experiments B and D.

We found that the U_{10m} data produce very small temperature impact. The T_l difference between experiments B and D is less than 0.2 K everywhere (not shown). We also found that the multi-variate impact of T_{2m} data <u>over sea</u> is small: less than 0.5 m/s everywhere (not shown). This is in agreement with the results in Fig 4a, which indicate that the uni-variate link between T_{2m} and T_l is very strong in typical sea-conditions (small z_0 and near-neutral stratification). Over land, however, the situation is different. The T_l analysis increments (for experiment A) over Eastern Europe are shown in Fig 5a, and the multi-variate impact on the wind field (experiment A minus C) is shown in Fig 5b. We can see that each maximum and minimum in the temperature increment field corresponds to a maximum in the wind impact. Comparing with the wind field itself (Fig 5c), we see that each maximum T_l-increment corresponds to an increase in the wind speed and each minimum corresponds to a decrease in wind speed. This is in accordance with the surface layer parametrization: We are in a day-time situation with an unstable boundary layer, in which increased turbulent mixing leads to an increase in near-surface air temperature. Observations indicating a warmer (colder) T_{2m} than the background can be fitted by the analysis either by increasing (decreasing) T_l or by increasing (decreasing) the wind speed, or both.

In section 4.1 we concluded that the current 3D-Var implementation is inappropriate for the use of T_{2m} data over land, because we effectively assume that the background T_s is perfect. Realistically, T_{2m} observations should to a large extent be fitted by modifying the model's T_s, and to a lesser extent T_l and U_l. The magnitudes in Fig 5a and 5b are therefore exaggerated. Allowing multi-variate observation operators is important for other data types , e.g. TOVS radiance data (*Eyre*, 1989; *Andersson et al*, 1994a), but for surface data we can conclude that the multi-variate aspects are of very little significance, at least as long as T_{2m} data are not used over land.

5. ASSIMILATION EXPERIMENTS

We have performed two different variational assimilations:

CONTROL using: p_s from SYNOP and DRIBU, (u,v) from AIREP, SATOB, TEMP and PILOT, T from AIREP and z from TEMP and PAOB.

SURF using the same set of observations as CONTROL plus (u_{10m},v_{10m}) from SYNOP, DRIBU, TEMP and PILOT and T_{2m} from SHIP and TEMP (over sea).

The assimilations consist of 5 days of 6-hour analysis cycles starting on 2 October 1992 at 1200 UT. For each assimilation we performed five 10-day forecasts starting on the 3th, 4th, 5th, 6th and 7th respectively. The 3D-Var scheme used has been described in section 2.

5.1 Analysis impact, land

After five days of assimilation the only significant impact of the wind and temperature surface data is over sea. Over land virtually all the analysis differences disappear during the 6-hour forecast of the assimilation (not shown). This can be due to a stronger physical forcing over land (mainly friction), or a problem with representativeness of the land surface observations. The verification of the ECMWF model against the observed 10 m wind speed shows a monthly bias over land of -2 m/s over Europe (*Strauss and Lanzinger*, 1992). The bias is larger in the neutral case, suggesting a roughness length problem. The negative wind speed bias can be explained by a combination of two factors: i) The model uses large values of z_0 (up to 50 m) over land, in order to represent the drag over mountain ranges (*Mason*, 1988); and ii) The wind stations have small characteristic values of z_0, due to the WMO standard specifications on local fetch and obstacles around the stations (*Beljaars*, 1987) giving an over-representation of stations in relatively flat surroundings. The wind speed bias can create analysis wind increments which are inconsistent with the information coming form pressure observations. Consequently the wind increments disappear in the 6-hour forecast.

5.2 Analysis impact, sea

In this section we present the results for 7 October 1992, 12 UT. We show, in Fig 6, the impact of SHIP data to the east of Asia; in particular the impact of one observation located at (46N, 163E). The analysis impact, as seen from the difference between the SURF and the CONTROL analyses, tend to decay with increasing height, due to the vertical correlation used by the variational analysis. They have virtually disappeared by 500 hPa. At 1000 hPa we find vector wind differences of 6 m/s (Fig 7a), corresponding to 15 m in geopotential height (Fig 7c). They decay to 3 m/s (Fig 7b) and 5 m (Fig 7d) at 850 hPa, and are virtually zero at 500 hPa (not shown).

A comparison with the operational OI analysis (T213, L31) truncated at T106 (labelled OPER), shows that SURF matches closer the operational analysis (which uses surface data in a simplified manner, as mentioned in section 4.3) than CONTROL does (Fig 8a and 8b). The vector wind differences to OPER at 1000 hPa are smaller in SURF by 5 m/s.

In the North Atlantic there are many SHIP observations located between 30 N and 50 N. Fig 9 shows the data available for the 7th October 1992, 12 UT. These data were used in the SURF assimilation but not in the CONTROL. The maximum vector wind differences between SURF and CONTROL at 1000 hPa are up to 10 m/s (Fig 10a) in the North Atlantic area, slightly decreased at 850 hPa (Fig 10b) and up to 3 m/s at 500 hPa (not shown). The corresponding differences in the mass field are +12 m and -7 m (not shown). Again, SURF is closer to the operational OI analysis than the CONTROL analysis is, as expected.

To summarize, the use of 10 m wind observations generally improves the analysis at the surface and in the lower troposphere. The wind increments are in approximate geostrophic balance with the mass increments. The 3D-Var analyses agree relatively well with the OI analyses provided surface data are used in both schemes.

5.3 Comparison with scatterometer data

Scatterometer data provide good quality independent surface observations against which an assimilation experiment can be verified (*Stoffelen et al*, 1992). We have compared the first guesses from the two different assimilations (CONTROL and SURF) against scatterometer data over the last 4 days of the experiments. For the Northern Hemisphere (north of 20 N), we calculated departure statistics of scatterometer wind minus the 10 m first guess wind from the ECMWF operational model (OPER), CONTROL and SURF experiments, respectively. On average the root mean square (rms) difference is roughly 2% smaller in SURF compared to the CONTROL and 3.6% smaller compared to the operational analysis. This indicates that the 3D-Var analyses using surface data (SURF) agrees more closely with the ERS-1 scatterometer data (which had not been used in the assimilations) than either the CONTROL or OPER analyses.

We have also compared some scatterometer wind patterns with corresponding CONTROL and SURF analyses, interpolated to the scatterometer observation points. We focused on areas where ship surface data were available at the time. In Fig 11a we show a swath of retrieved scatterometer winds in the North Atlantic (55-50 N) for 7 October 1992 at 00 UT. When comparing these observations with the wind field from the CONTROL (Fig 11b) and SURF (Fig 11c) experiments, we find that the observed front (Fig 11a) is similar to the analysed front in SURF; both are sharper than in the CONTROL analysis.

Fig 12a shows a cyclonic circulation in the Southern Hemisphere, 6 October 1992 at 1800 UT, at (30S, 160W) observed by ERS-1, which is absent in the CONTROL analysed wind field (Fig 12b) and well represented in the SURF analysis (Fig 12c).

The results presented in this section show that there is a clear positive impact on the analysed near-surface wind field from the use of surface observations over sea. The 3D-Var assimilation using surface data is closer to ERS-1 scatterometer data than the CONTROL assimilation. This result is not surprising since there is a general agreement between ERS-1 and SHIP data (*Stoffelen et al*, 1992). However, it demonstrates that the 3D-Var method works and extracts useful information from the conventional surface data. More importantly, we found that the 3D-Var analysis agrees slightly closer to the ERS-1 data than the operational OI analysis does.

5.4 Forecast impact

Forecasts were run from 12 UT each day of the analyses of the SURF and CONTROL assimilations, respectively; a total of 5 forecasts from each experiment. We verified the forecasts against the operational ECMWF OI analyses.

We found that the forecast impact is very small and tends to disappear after 24 hours. In Fig 13 we compare the geopotential height 24 hour forecast from 7 October 1992 at 12 UT against the operational ECMWF analysis. The 24 hour geopotential height forecast errors (i.e. forecast minus verifying analysis) in the central North Atlantic are shown for CONTROL (Fig 13a) and SURF (Fig 13b). The maximum errors are 10 m smaller at 1000 hPa in the forecast from the SURF analysis - and at 850 hPa they are 5 m smaller (not shown). The vector wind forecast errors are also slightly larger in CONTROL than in SURF (not shown). After 48 hours this small positive impact disappears.

The root mean square error (in verification against the operational ECMWF analyses) of the 1000 hPa wind vectors averaged over the five forecasts is smaller for SURF than for CONTROL in the short range forecast in the North Pacific (Fig 14a) and the North Atlantic (Fig 14b). A smaller error is also observed in the scores in the Tropics for wind at 1000 hPa and geopotential height at 1000 and 500 hPa (not shown). The impact beyond day 2 of the forecasts favour CONTROL slightly. The 1000 hPa wind scores for the Northern (Fig 14c) and the Southern Hemisphere (Fig 14d) also show a positive impact at the very short range, and a slightly negative impact in the medium range.

The anomaly correlation for geopotential height at 1000 and 500 hPa in both hemispheres show a slightly negative impact of the surface data beyond day 3 of the forecasts (not shown), similar to the result in terms of wind rms error.

The relatively small sample of forecasts (5 cases) may not be enough to asses the impact of the surface data on the medium range. We are nevertheless confident with the positive impact in the short range. More extensive experimentation to accurately asses the impact of the data in the medium range will be carried out when the final configuration of 3D-Var has been established.

6. DISCUSSION AND CONCLUSIONS

The use of surface observations in a three-dimensional variational analysis has been developed. Two-metre temperature and ten-metre wind data have been assimilated, using a non-linear multi-variate observation operator.

The results show that with the current implementation of 3D-Var, 2 m temperature cannot successfully be assimilated over land. This is because the control variable does not include surface fields, in particular surface temperature, which then cannot be updated during the minimisation. We have shown that this can lead to unrealistic changes in the near surface stratification. In order to assimilate 2 m temperature over land, a future simplified implementation may consist of keeping the difference $\Delta\theta_v$ in the formula (3.3) constant during the minimisation procedure (*Coiffier et al*, 1987).

In contrast to the simpler method of assigning the observation minus first guess departure directly to the lowest model level (as employed by NMC SSI, *Parrish and Derber*, 1992) or to the reported pressure (ECMWF OI, *Lorenc*, 1981), our method gives a modulation of the analysis weight, which depends primarily on the model's near-surface stratification and the surface roughness at the observation location. The weight decreases, in general with increased surface roughness. In the very stable cases, the relationship between temperature at 2 m and at the lowest model level (typically 30 m) is so weak that the data should have very little influence on the analysis. This is automatically taken into account in the full 3D-Var scheme, as demonstrated in section 4.3. On the other hand, in the unstable case, for small values of the roughness length, the simplified and the full method give similar results, as there is, in those conditions, a high correlation between the observed and the analysed quantities.

The multi-variate aspects of the observation operators are taken into account in a consistent way, in 3D-Var, through the adjoint technique (*Pailleux et al*, 1991). Ten metre wind observations, to some extent, provide information on low-level temperature, and similarly, 2 m temperature data provide information on the low-level wind speed, according to the surface-layer parametrization. We found, however, that this is of minor importance (except for T_{2m} observations over land, which we propose not to use). This is because the direct (uni-variate) link is strong (as shown in Fig 4a and 4b) for wind in all conditions, and for temperature in the conditions typical over sea (small roughness, and near-neutral or unstable stratification).

We have shown that surface observations have a positive impact in the analysis over sea. Over land the increments decay during the 6-hour forecast within the assimilation cycle. This may be due to a stronger friction over land or to a problem of representativeness of the land surface observations, as discussed in section 5.1 and by *Strauss and Lanzinger* (1992). Over sea, on the other hand, we noticed a positive impact in the wind field, with matching increments in the mass field.

The surface increments are decreasing with height, vanishing at 500 hPa. There is therefore little propagation of information into the free atmosphere. This is a consequence of the analysis not being flow-dependent. A more effective analysis of the surface data is expected with the four-dimensional variational scheme (*Thépaut et al*, 1993). For the J_b formulation used in these experiments it is assumed that only 5% of the 6-hour forecast error is in the divergent part of the wind field, at all levels of the model, although we know that there is a higher proportion of divergence near the surface. Furthermore, the background term is barotropic. It decreases the magnitude of the analysis increments with height but is not able to turn the wind increments with height, since friction is not taken into account. The analysis of the free atmosphere is thus not dynamically consistent with the surface data.

Surface observations improve the quality of the analysis in the lower troposphere, over sea. In the forecast, the impact does not last more than 24 hours: the extra-tropical scores show a slightly negative impact beyond that range. This work was carried out in the context of a continually developing 3D-Var scheme. Ongoing improvements of primarily the background term may lead to a more sustained forecast impact.

More extensive experimentation is needed for a more accurate assessment of the impact of surface data on the medium-range forecast.

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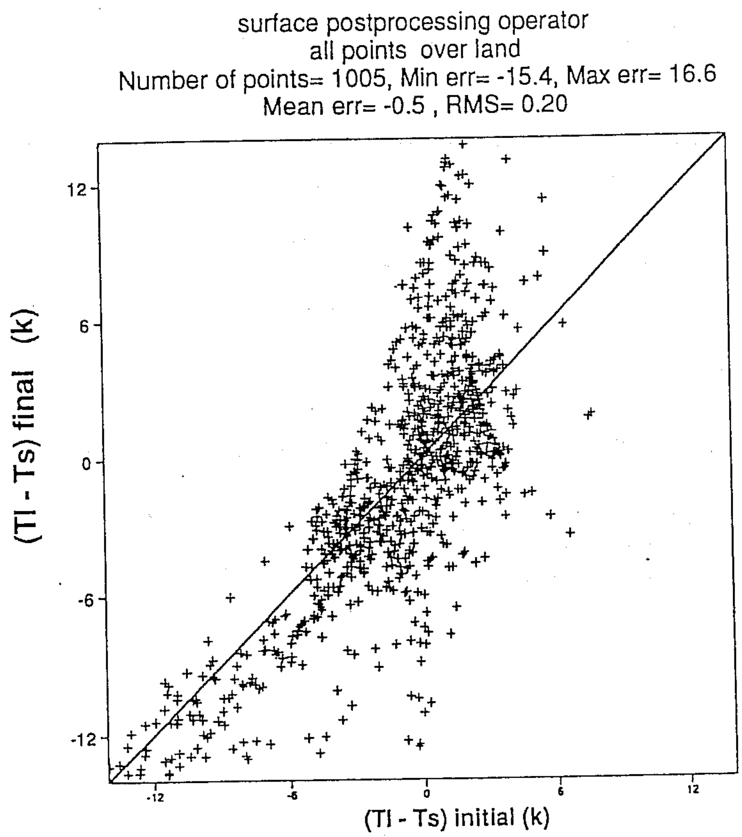


Fig 1 Scatter plot of the difference between the temperature at the lowest model level and at the surface ($T_l - T_s$), for land points. The horizontal axis shows initial point of minimization (first guess). The vertical axis shows final point of minimization (analysis).

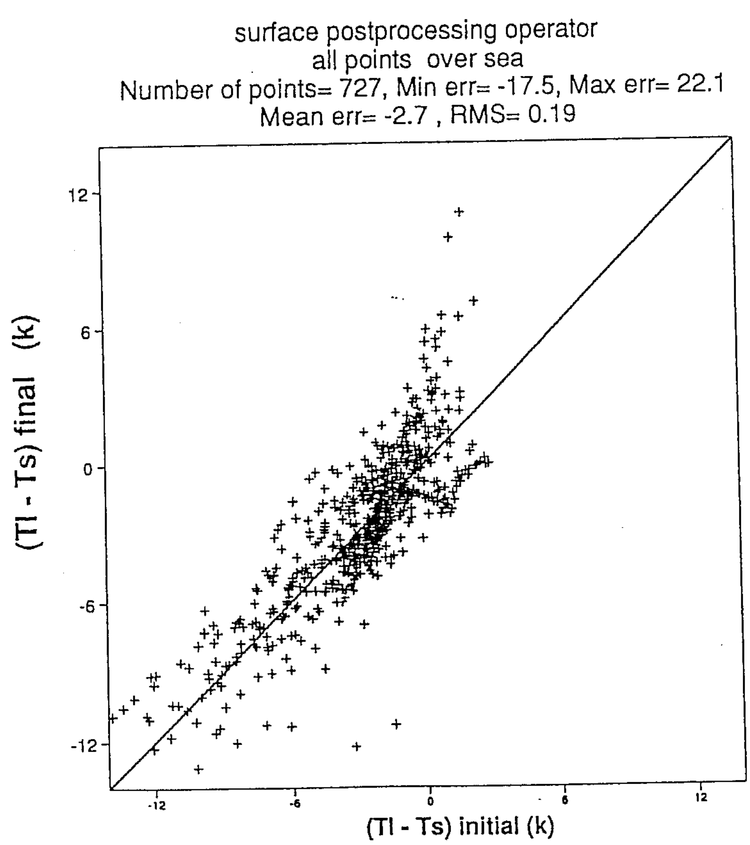


Fig 2 Like Fig 1 for sea points.

surface postprocessing operator
all points over sea
Number of points= 518, Min err= -10.6, Max err= 3.7
Mean err= -1.7 , RMS= 0.12

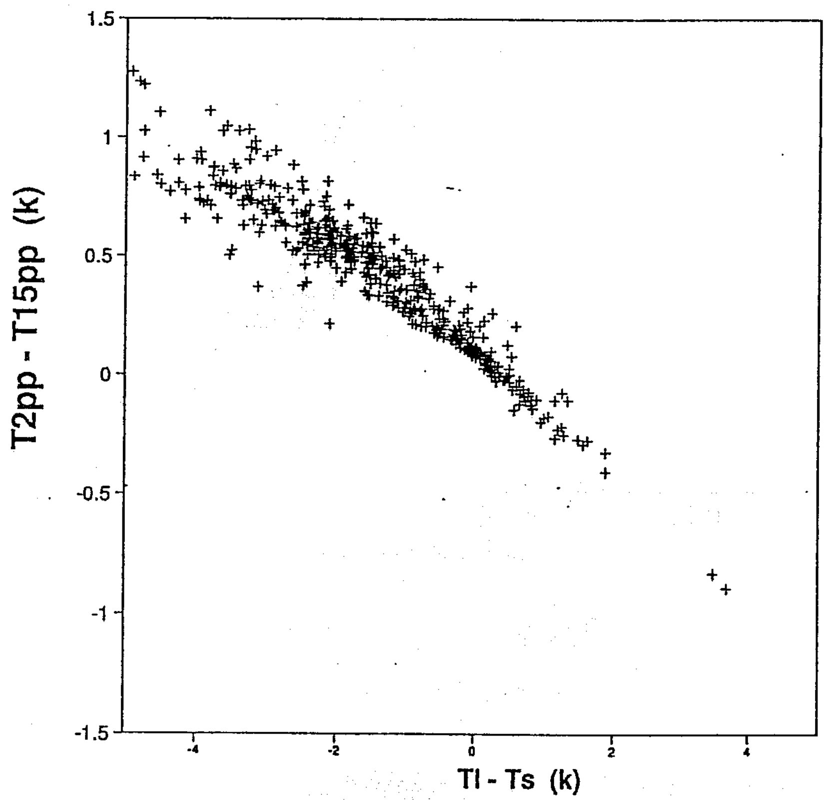
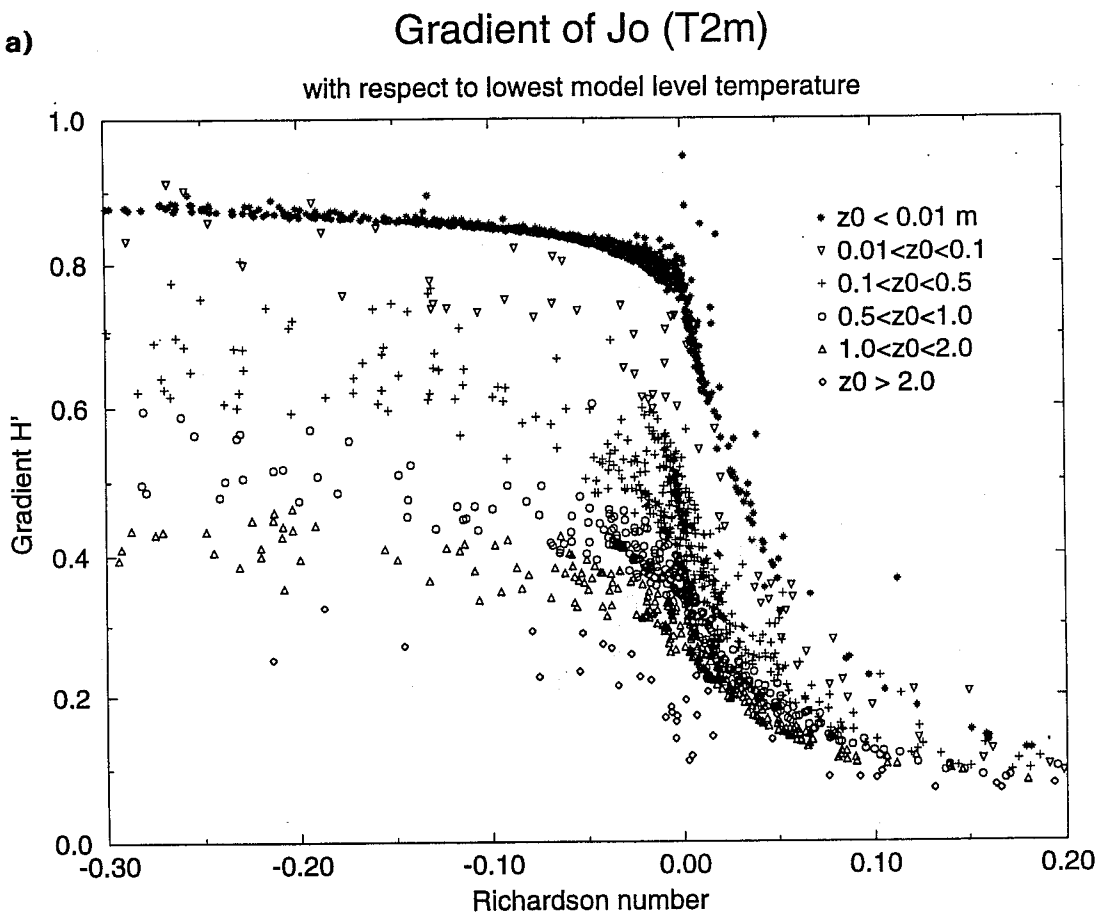


Fig 3 Difference between the analysed temperature estimated at two different station heights (2 m minus 15 m) versus the difference between lowest model level temperature and surface temperature.

a)



b)

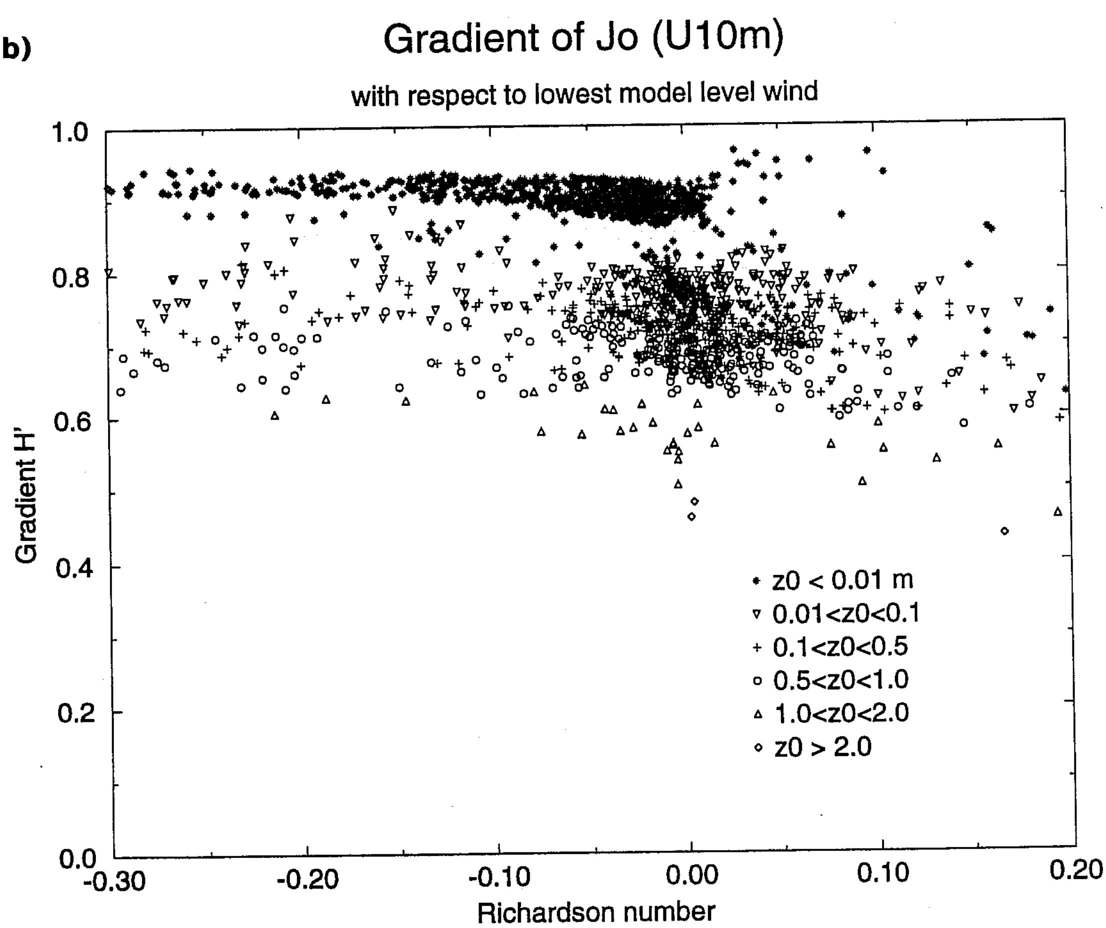
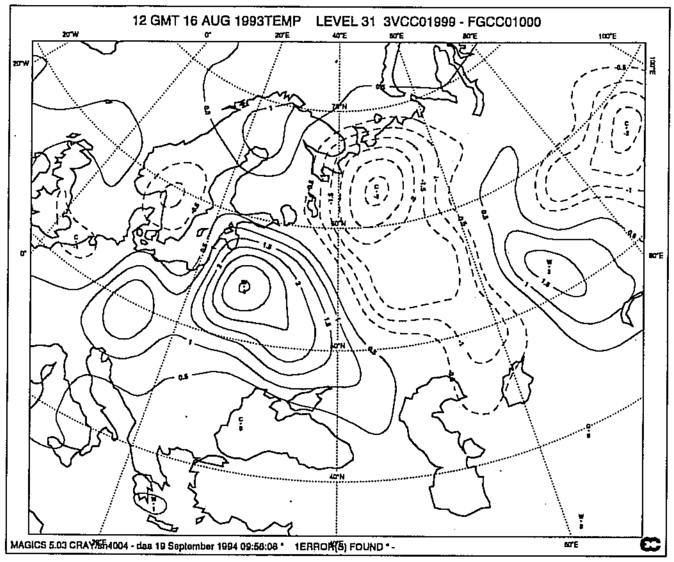
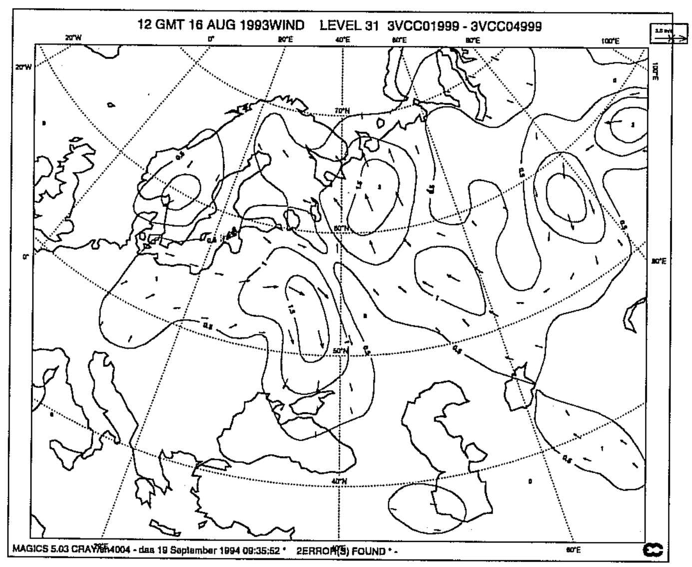


Fig 4 Partial derivative of H with respect to the lowest model level, versus the bulk Richardson number. for all observations within one 6-hour period. a) shows $\partial H_2 / \partial T_{2m}$ and b) shows $\partial H_1 / \partial u_{10m}$.

a)



b)



c)

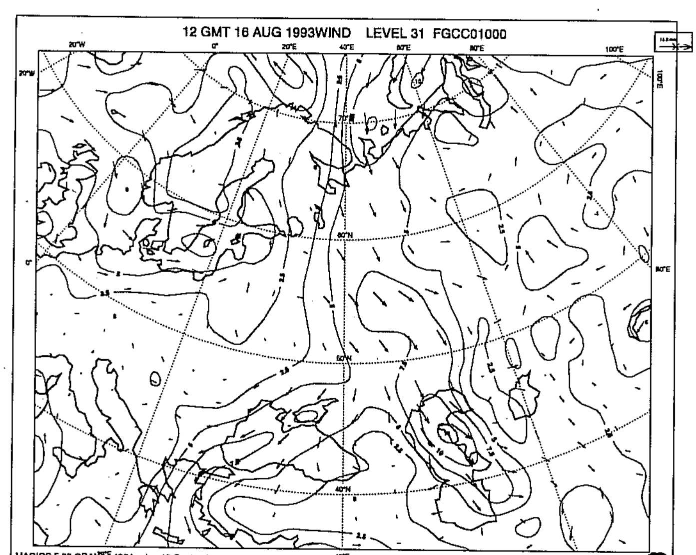


Fig 5 Using T_{2m} data only (19930816-12 UT), a) shows T_l increments (with 0.5 K contour interval), b) shows multi-variat impact on U_l, i.e. the difference between an analysis using the multi-variate operator and one using the uni-variate operator (0.5 m/s) and c) the corresponding wind field of the background (2.5 m/s).

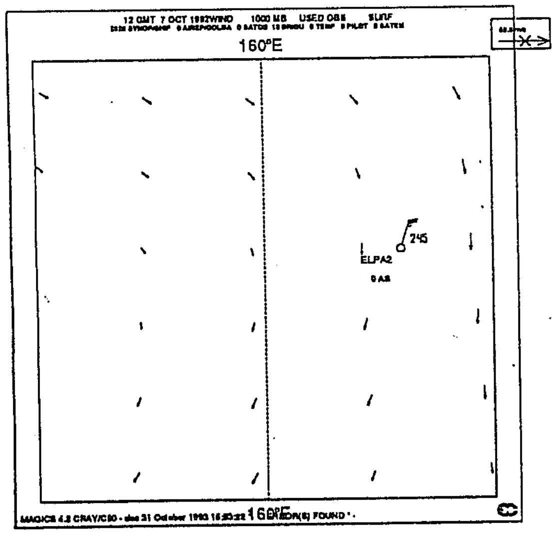


Fig 6 Analysed wind field at 1000 hPa at the end of the assimilation period (19921007-12 UT) in SURF experiment with one SHIP wind observation at the location (46 N, 163 E).

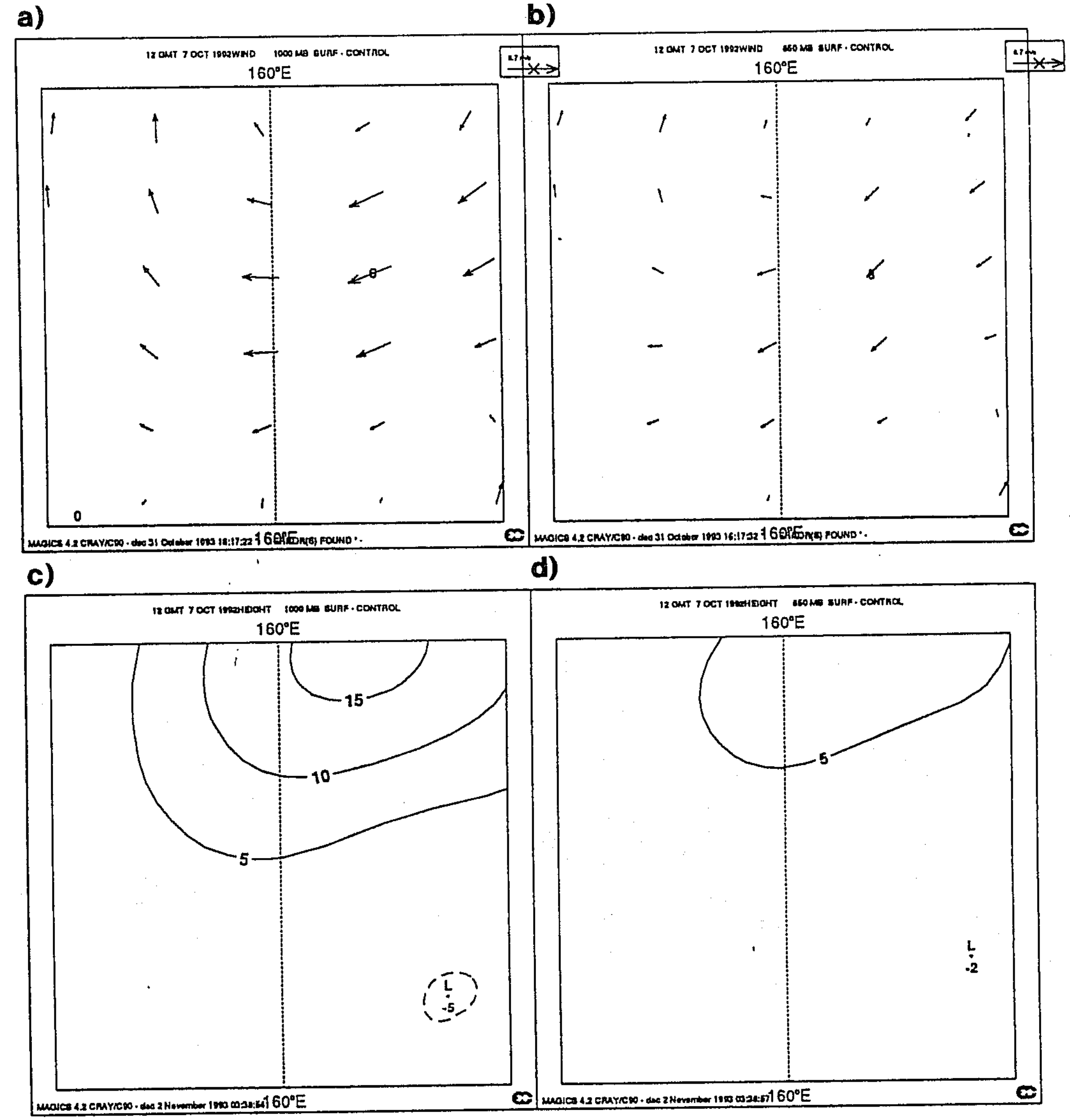


Fig 7 Analysis differences between two 3D-Var assimilations: SURF minus CONTROL, corresponding to Fig 6. a) shows 1000 hPa wind, b) is 850 hPa wind, c) is 1000 hPa height and d) is 850 hPa height. Contour interval is 5 m.

a) b)

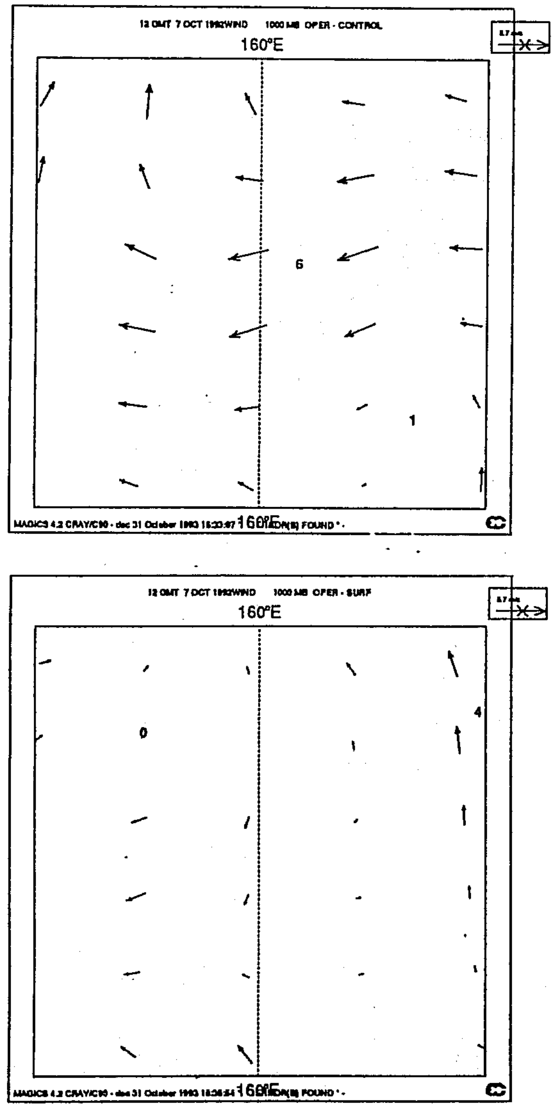


Fig 8 Wind field differences at 1000 hPa corresponding to Fig 6 and Fig 7, for a) OI operational analysis at T213L31, truncated at T106, minus CONTROL (3D-Var assimilation at T106L19) and b) OI operational analysis minus SURF.

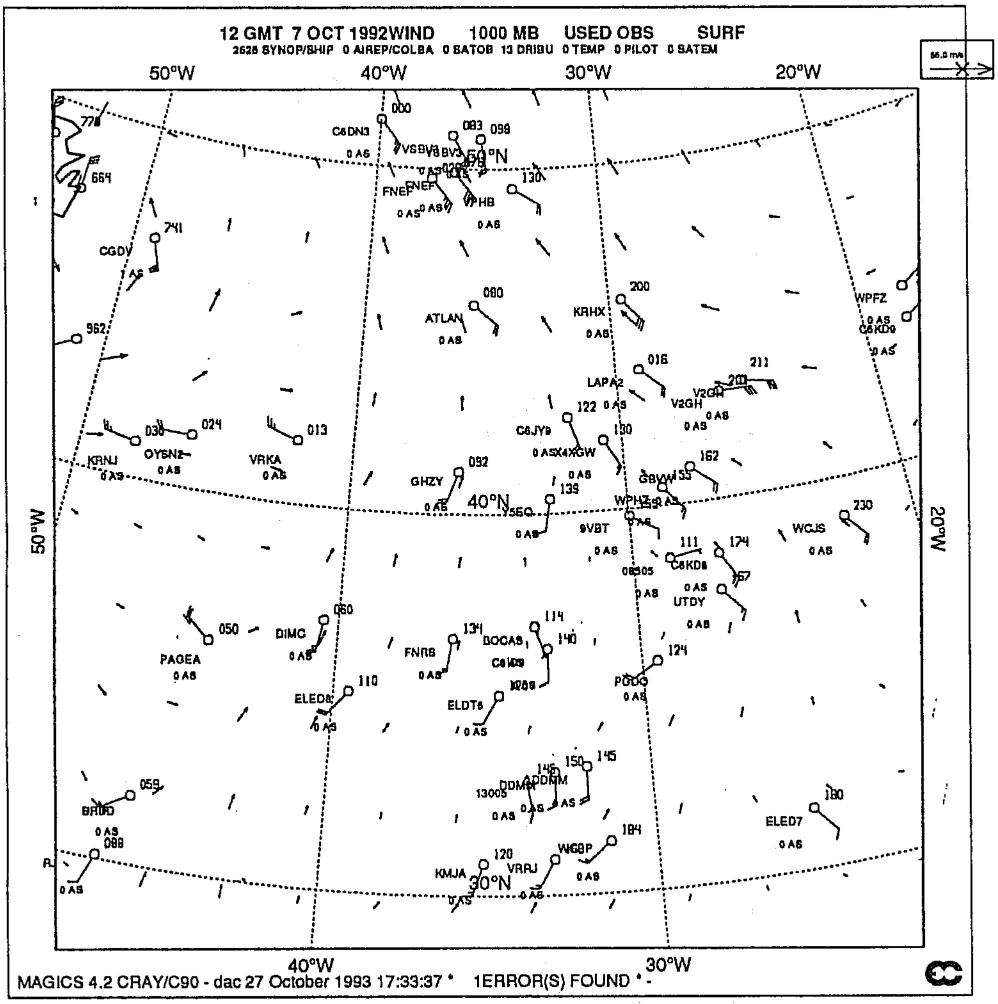
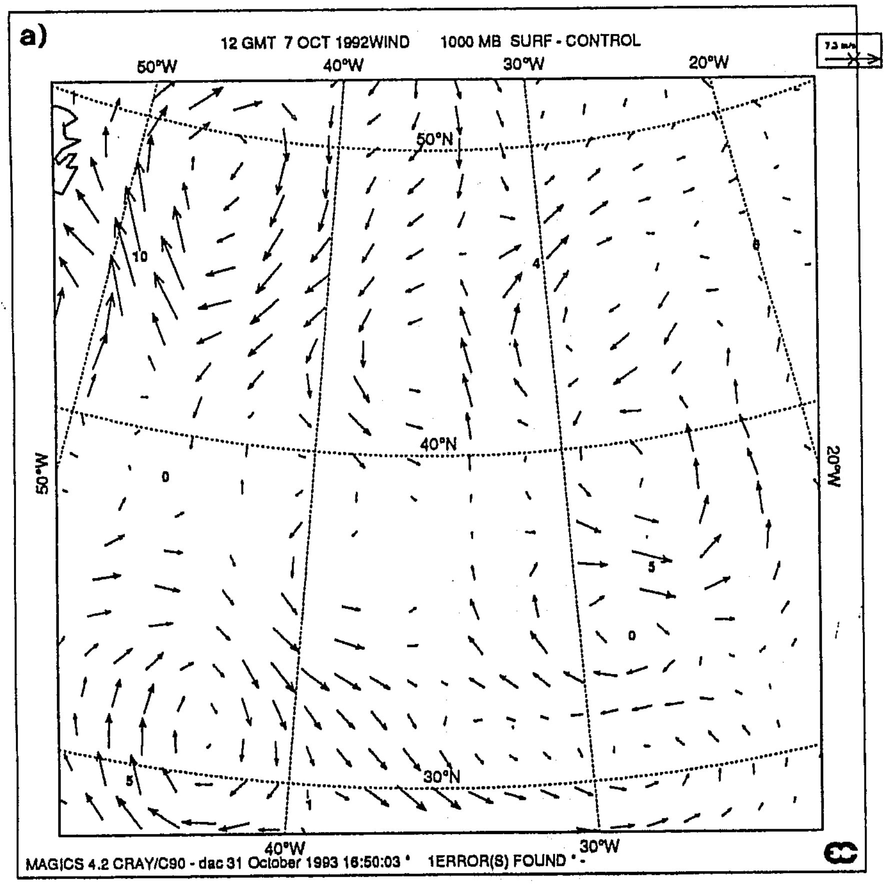


Fig 9 Wind field at 1000 hPa at the end of the assimilation period (19921007-12 UT) in SURF experiment with several SHIP wind observations, for the area between 50-30N and 50-20W.

a)



b)

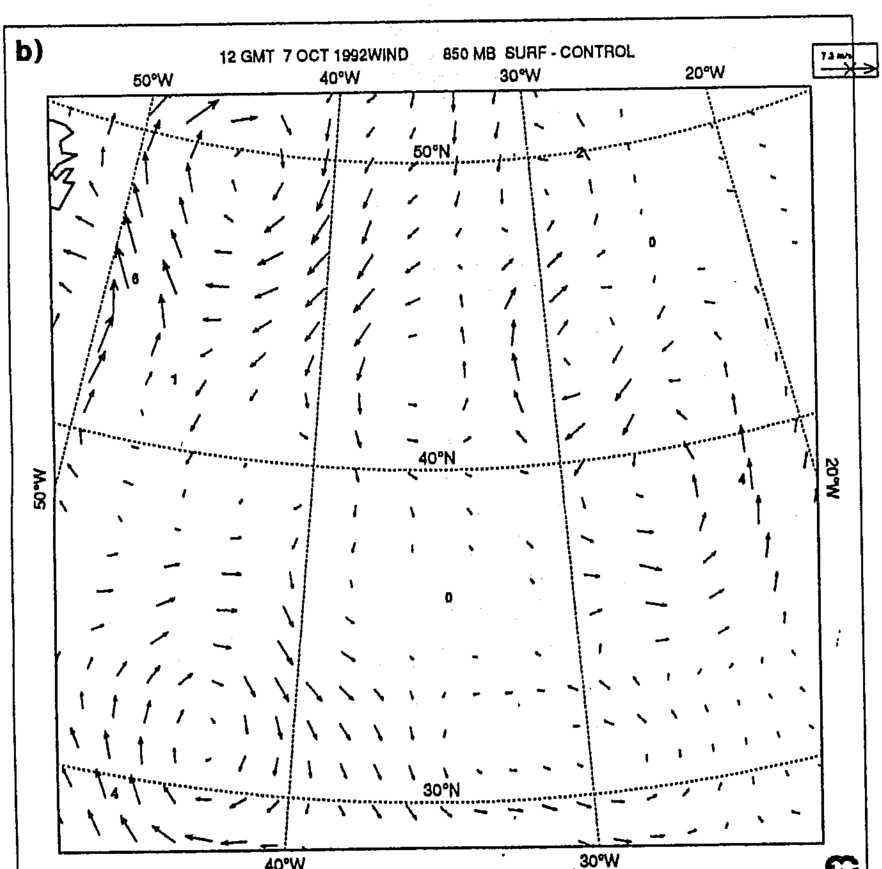


Fig 10 Wind analysis differences (SURF minus CONTROL) corresponding to Fig 9. a) shows 1000 hPa and b) shows 850 hPa.

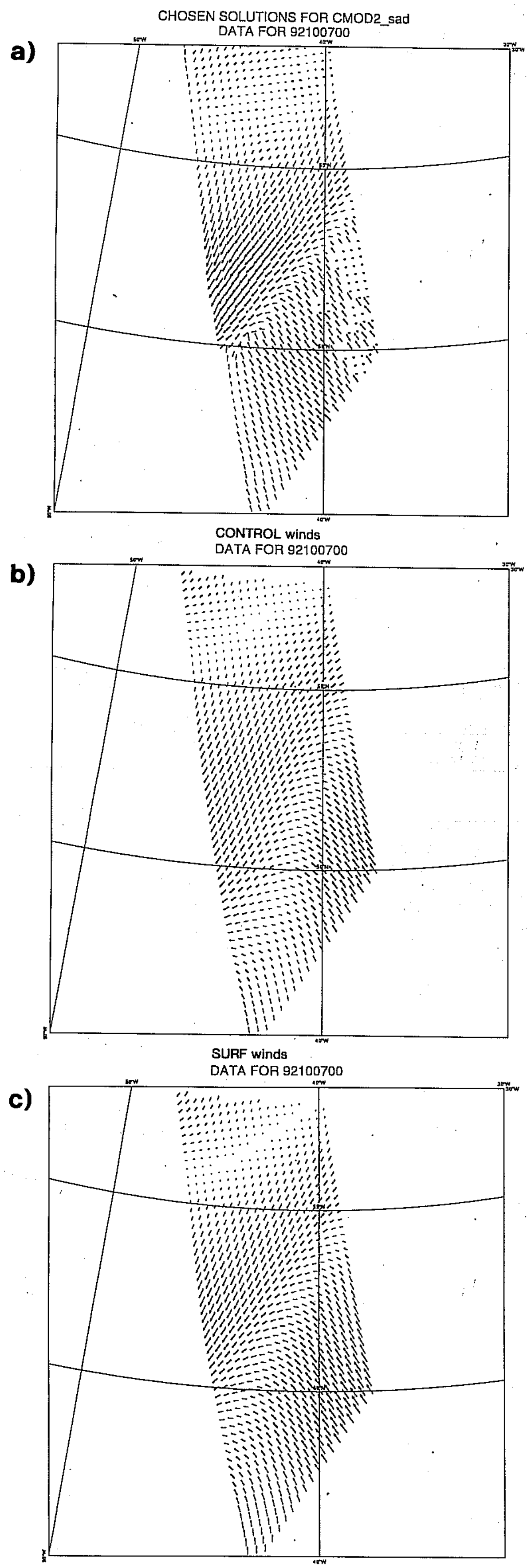


Fig 11 ERS-1 scatterometer data for 19921007-00 UT located between 60-45N and 48-38W. a) shows the retrieved scatterometer wind, b) shows the CONTROL analysed wind field interpolated to the scatterometer locations and c) shows SURF.

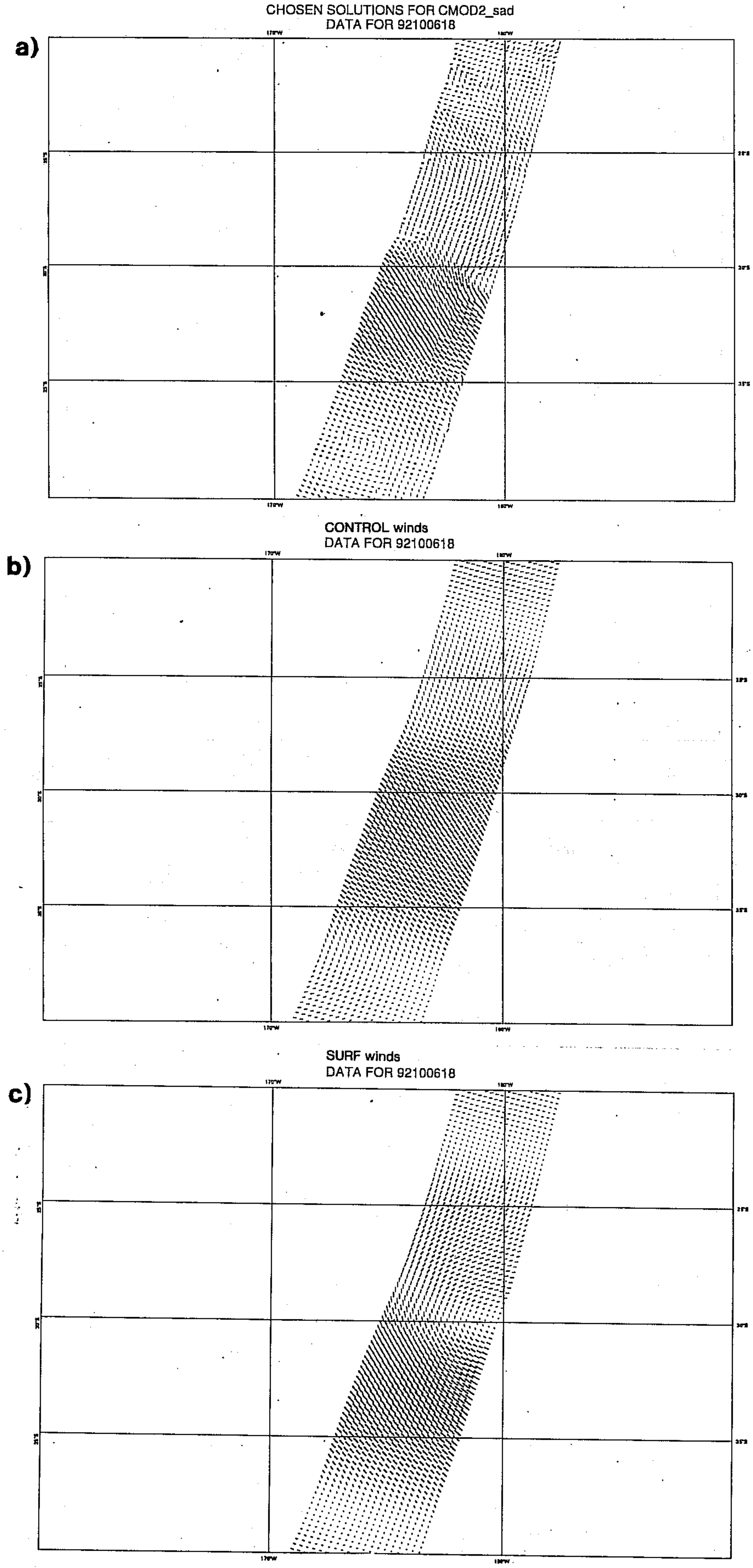
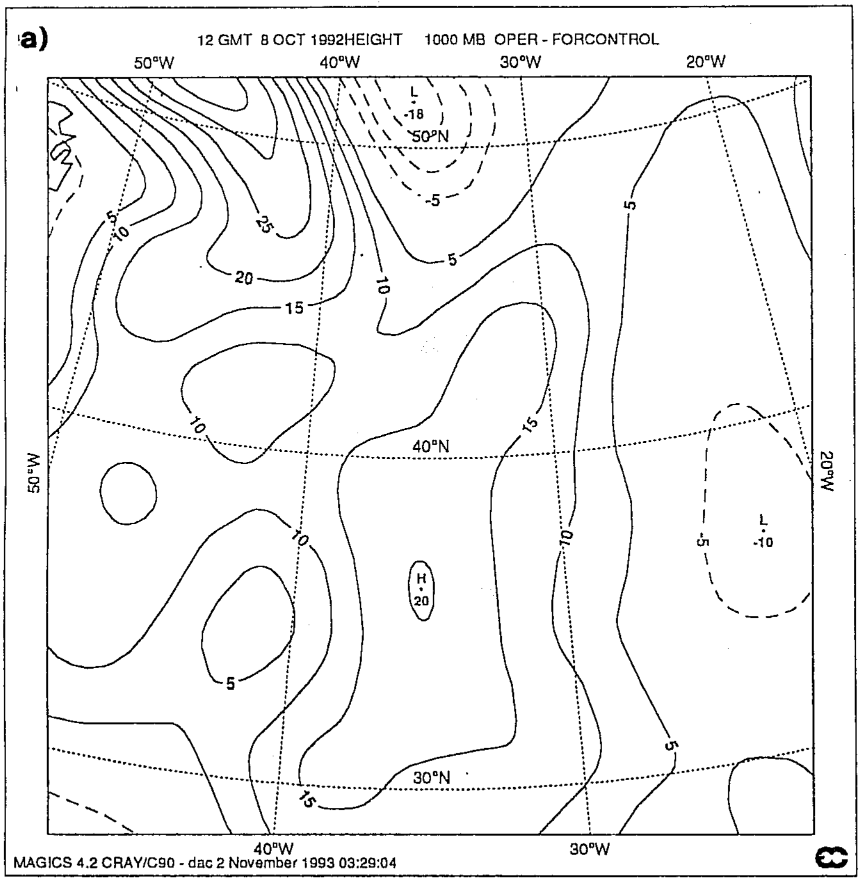


Fig 12 ERS-1 scatterometer data for 19921006-18UT, located between 20-40N and 168-158W. Otherwise like Fig 11.



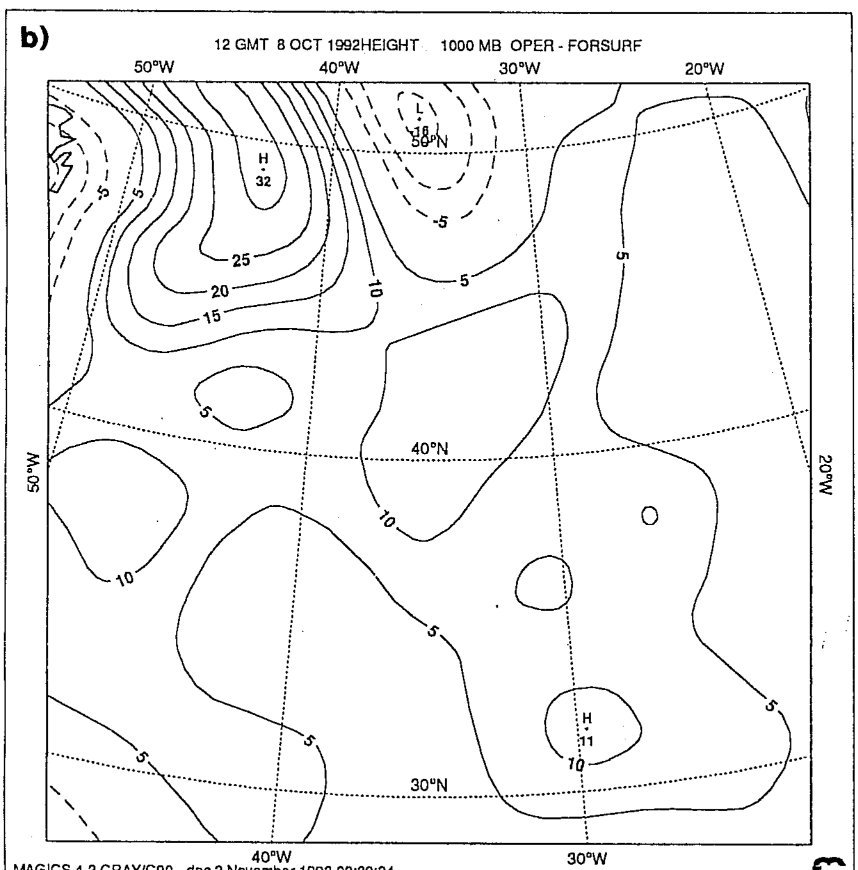


Fig 13 24-hour forecast errors in forecasts starting at 19921007-12 UT. The verifying analysis is OI operational analysis at T213L31, truncated at T106. a) shows CONTROL and b) shows SURF. Contour interval is 5 m.

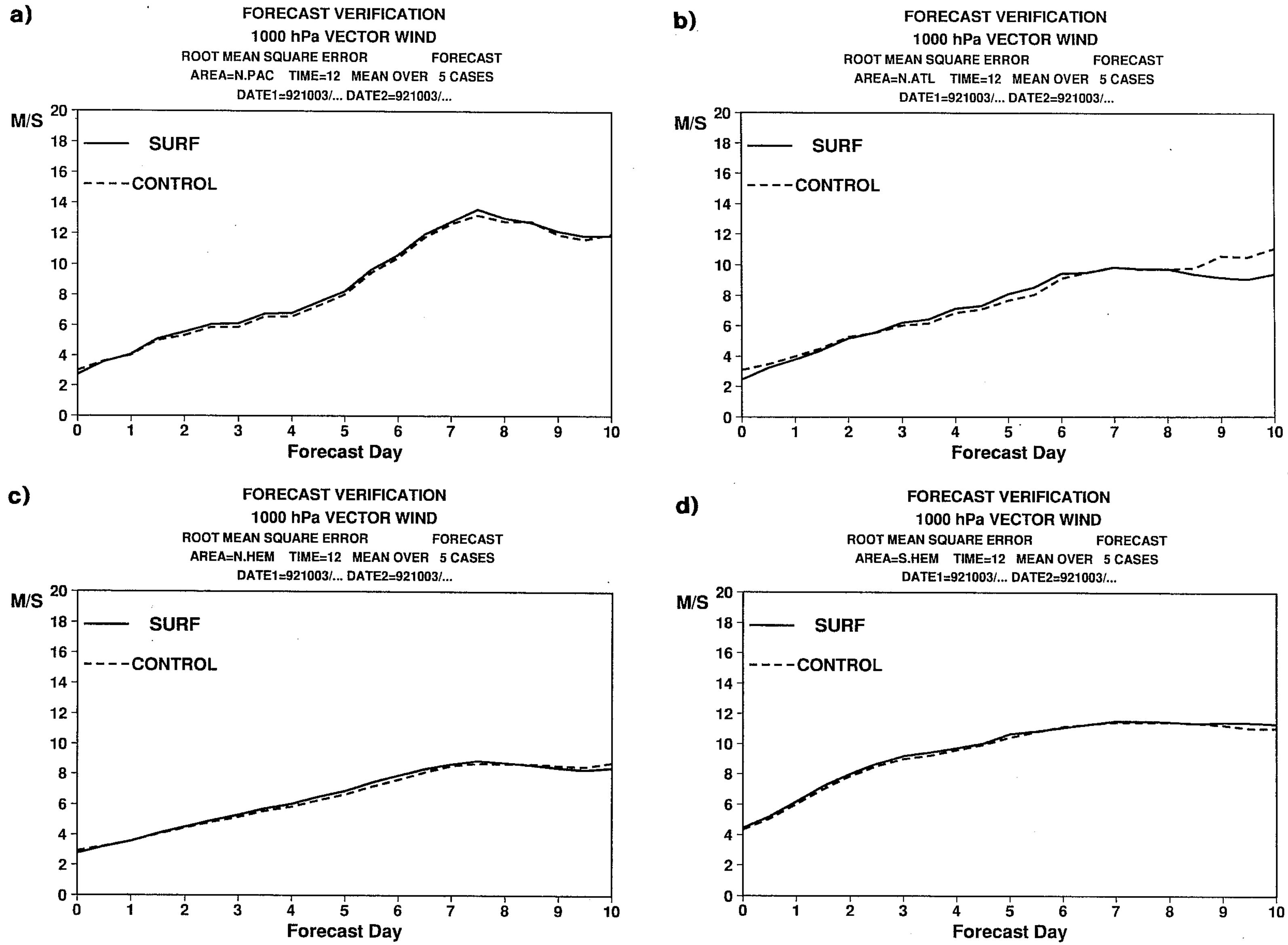


Fig 14 Average root mean square forecast error for vector wind at 1000 hPa for four different areas: a) North Pacific, b) North Atlantic, c) Northern Hemisphere and d) Southern Hemisphere.