Forecasting the Surface Weather Elements with a Local Dynamical-Adaptation Method Using a Variational Technique

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(Manuscript received 25 July 1991, in final form 25 September 1991)

ABSTRACT

A simple method of dynamical adaptation of a mesoscale model has been tested to produce meteorological parameters locally adapted at meteorological stations. This method is based on the use of a soil model in association with a surface boundary-layer model (MUSCLES, modélisation uni-dimensionnelle du sol et de la couche limite en surface), coupled with the outputs of the French operational mesoscale model (PERIDOT). The meteorological station-dependent characteristic constants used for describing the soil properties are identified by comparisons with observations. This adjustment is achieved by a variational method consisting in minimizing a cost function that measures the distance between the output parameters computed by MUSCLES and the observed ones. The minimization algorithm developed for that purpose requires the computation of the gradient of this cost function, which is done in practice by using the adjoint of the MUSCLES code.

For forecasting purposes, it was found that the best way is to adjust the local constants by computing the cost function on the ten previous days. The results are encouraging; for five of the six stations considered, the quality of the gains is significant, even if they are lower than what is achieved by the operationally used statistical adaptation.

1. Introduction

Over the last few years, important improvements have been achieved in numerical weather prediction. This allows the forecaster to directly use the outputs of numerical weather prediction models in order to forecast the surface weather elements (2-m temperature and humidity, 10-m wind, etc.).

At the French National Weather Service (METEO-France), the forecasts of the limited-area model PERIDOT (35-km grid size) are used for that purpose. The 2-m temperature and humidity and the 10-m wind velocity are routinely compared with observations at the nearest meteorological station. These PERIDOT forecasts should be considered as average values over the grid mesh. However, a study of the variability at the subgrid scale for the PERIDOT grid near Paris has shown that the mean absolute difference over 1 year between the measurements made in two different meteorological stations inside this mesh is 1 K for the 2-m temperature, 0.0005 kg kg^{-1} for the 2-m humidity, and 2 m s^{-1} for the 10-m wind speed (Juvanon Du Vachat et al. 1988). These scores, compared with the mean absolute error of PERIDOT forecasts for the same stations (2 K, 0.0009 kg kg^{-1}, 2.5 m s^{-1}), show that roughly one-half of the forecast error can be assigned to local inhomogeneity. The purpose of this paper is to reduce this portion of the error.

For that, two different but complementary approaches can be envisaged. First, a statistical approach is attempted: this technique consists in determining the appropriate predictors on a learning file and in defining a judicious linear combination of these predictors to forecast the meteorological parameters. This technique, already used at METEO-France, is of good quality for the 2-m temperature prediction (Pottier et al. 1989; Pottier 1991). Second, a local dynamical interpretation is used: this technique consists in describing explicitly the physical mechanisms involved in the evolution of the output parameters, where the upper-air PERIDOT forecast is taken as boundary condition. This second approach is the subject of this paper.

In this domain, one-dimensional boundary-layer models coupled with large-scale three-dimensional models have been used to predict the vertical structure of the atmosphere over a defined locality (Burk and Thompson 1982; Musson-Genon 1989; Louis, personal communication) or along a trajectory (Reiff et al. 1984). In order to predict only parameters that can be verified, the entire modelization of the atmospheric boundary layer is not necessary. This is why a simpler

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method, based on a one-dimensional modelization of the soil and of the surface boundary layer (French acronym MUSCLES: modélisation uni-dimensionnelle du sol et de la couche limite en surface) has been tested here.

This model, coupled with the limited-area model PERIDOT, describes the evolution of the soil parameters and of the surface boundary-layer parameters with the same algorithms as in the PERIDOT model. This computation is, however, made outside of PERIDOT and with a different set of data for the local constants describing the soil characteristics. These constants are chosen in order to minimize the prediction error for the meteorological station considered. The adjustment of the local characteristic constants (roughness length, albedo, emissivity, etc.) is carried out by using variational techniques that require the development of the adjoint of the MUSCLES model. The originality of this study lies in the use of a variational method in the context of operational forecasting of meteorological parameters, with the expectation of the important operational applications.

In section 2, the equations of the MUSCLES model will be presented. In section 3, we will describe the method that has been used to optimize the local characteristic constants, and in section 4, preliminary results will be shown.

2. The equations of the MUSCLES model

The MUSCLES parameterization is the same as the parameterization of the soil–atmosphere interface of our operational model PERIDOT.

The MUSCLES model is divided in three distinct parts:

1) the evolution of the soil temperature and liquid water content of the ground,

2) the determination of the turbulent fluxes of momentum and of sensible and latent heat at the soil–atmosphere interface, and

3) the determination of the output parameters (2-m temperature and humidity, 10-m wind).

Each part will show the system of equations that has been used, the forcing by the PERIDOT model, and the local characteristic constants to be adjusted.

a. The equations for soil parameters

1) Soil-temperature evolution

The soil-temperature evolution at the soil–atmosphere interface is driven by an energetic balance for a skin layer of zero thickness. Assuming the diurnal variation of the surface temperature to be a sinusoidal function of the time in order to parameterize the heat flux in the ground, it is possible to derive a simple evolution equation for the surface temperature following Bhumralkar (1975) and Deardorff (1978). The solution used is described in Coiffier et al. (1987);

$$\frac{dT_s}{dt} = C_{\text{soil}} H_{\text{at}} - \frac{2\pi}{t_1}(T_s - T_p), \qquad (1)$$

where C_{soil} denotes a thermic coefficient of the ground tuning the amplitude of the diurnal variation of the surface temperature T_s, $t_1 = 86\,400$ s is the time constant of diurnal evolution, T_p is a restore term toward a kind of running average of T_s, and H_{at} is the total energetic flux which can be written as

$$H_{\text{at}} = (1 - A)R_s + \epsilon R_t - \text{Ro}C_pQ_0 - \text{Ro}LE_0 - \epsilon\sigma T_s^4. \qquad (2)$$

Here A is the albedo, R_s is the downward solar radiative flux, ϵ is the emissivity, R_t is the downward thermic radiative flux, Ro is the density of the air near the ground, Q_0 is the surface value of the kinematic heat flux in the atmosphere, $C_p = 1005.46$ J K^{-1} kg^{-1} is the specific heat at a constant pressure for the air, $L = 2\,500\,800$ J kg^{-1} is the latent heat of vaporization of water, E_0 is the surface value of the kinematic evaporation flux in the atmosphere, and $\sigma = 5.67 \times 10^{-8}$ W m^{-2} K^{-4} is the Stefan constant.

The PERIDOT model also uses an evolution equation of T_p. Yet considering the very weak variation of T_p throughout 24 h, it is useless for the MUSCLES model to compute another evolution equation.

The parameters A, ϵ, and C_{soil} are local characteristic constants. Terms R_s, R_t and T_p are given by the PERIDOT forcing. The fluxes Q_0 and E_0 are computed from the equations presented in section 2b according to the Monin–Obukhov theory.

2) Soil-humidity evolution

The evolution of the soil liquid water content is deduced from the same principles as the surface temperature, according to Coiffier et al. (1987):

$$\frac{dW_1}{dt} = \frac{P_r - \text{Ro}E_0}{C_1} - \frac{W_1 - W_2}{t_1}$$
$$\frac{dW_2}{dt} = \frac{C_2(W_1 - W_2)}{t_1}, \qquad (3)$$

where P_r is the precipitation flux, $W_1 = W_s/W_{s\max}$ is a nondimensional liquid water content with W_s the liquid water content for the surface reservoir and $W_{s\max}$ its maximum value, and $W_2 = W_p/W_{p\max}$ is a nondimensional liquid water content with W_p the liquid water content for the deep reservoir (which does not contain the surface reservoir) and $W_{p\max}$ its maximum value.

While a single equation is used for the temperature, two equations are used for the liquid water contents, because their evolutions may be rather sharp in case of precipitations.

This formula allows one to introduce only two local characteristic constants: $C_1 = W_{s\max}/C_{w\text{soil}}$ and $C_2 = W_{s\max}/W_{p\max}$, where $C_{w\text{soil}}$ is a nondimensional constant tuning the depth of the reservoirs, and $W_{s\max}/W_{p\max}$ is a nondimensional constant tuning the ratio of these depths.

The surface specific humidity is computed as a function of W_1, which varies according to the nature of the surface (bare soil or soil covered by vegetation). By using "desert" as the bare soil fraction,

$$q_s = \text{Hu}\, q_{\text{sat}}(T_s, P_s) + (1 - \text{desert})(1 - \text{Hu})q, \quad (4)$$

where $\text{Hu} = 0.5[1 - \cos(\pi W_1)]$, q_{sat} is the saturated value of q_s, and q is the specific humidity of the air above the soil. Here Hu will be equal to 1 when a dew flux is present.

Equation (4), which is rather empirical, results from a compromise between the use of the Halstead parameter for the soils covered by vegetation and the use of the relative humidity for the bare soils.

In these equations, C_1, C_2, and desert are local characteristic constants. The precipitation flux P_r and the specific humidity q are given by the PERIDOT forcing. The kinematic evaporation flux E_0 can be calculated using the equations presented in subsection 2b.

Equations (1) and (3) are solved using the Crank–Nicholson numerical scheme with a time step of 10 min, where the nonlinear terms of these equations are linearized.

The solution of these equations needs to compute the kinematic fluxes E_0 and Q_0 in the MUSCLES model because these fluxes are strongly dependent on the surface parameters (T_s and q_s), which will be computed with a local characteristic constants dataset different from that of PERIDOT.

b. Flux determination in the surface boundary layer

In the surface boundary layer, the flow near to the ground can be considered as quasi-stationnary and the Coriolis and pressure gradient forces are negligible. Following the Monin–Obukhov theory and according to Louis (1979), who suggested that a bulk Richardson number (Ri) should be used instead of the Monin–Obukhov length (Lmo), the following system of equations is used:

$$U^{*2} = a^2U^2F_u[(z + z_0)/z_0, \text{Ri}]$$
$$Q_0 = a^2U[\Theta(z) - \Theta_s]F_\Theta[(z + z_0)/z_0), \text{Ri}]$$
$$E_0 = a^2U[q(z) - q_s]F_\Theta[(z + z_0)/z_0), \text{Ri}], \quad (5)$$

where U^* is the friction velocity, U is the wind speed, $\Theta(z)$ is the potential temperature, and $q(z)$ is the specific humidity at z level. Also, $a = k_a \ln[(z + z_0)/z_0]$ with $k_a = 0.4$ the von Kármán constant, $\text{Ri} = gz\{[\Theta(z) - \Theta_s](\Theta_m U^2)^{-1}\}$ with g the gravitational acceleration, Θ_m is the average potential temperature, and z_0 is the roughness length. Here the functions F_u and F_Θ are chosen according to Louis et al. (1982):

stable case: $\text{Ri} > 0$

$$F_u = [1 + 2b\,\text{Ri}(1 + d\,\text{Ri})^{-1/2}]^{-1}$$
$$F_\Theta = [1 + 3b\,\text{Ri}(1 + d\,\text{Ri})^{1/2}]^{-1} \quad (6)$$

unstable case: $\text{Ri} < 0$

$$F_u = 1 - 2b\,\text{Ri}\{1 + 3ba^2c[(z + z_0)\,\text{Ri}/z_0]^{1/2}\}^{-1}$$
$$F_\Theta = 1 - 3b\,\text{Ri}\{1 + 3ba^2c[(z + z_0)\,\text{Ri}/z_0]^{1/2}\}^{-1} \quad (7)$$

with $b = c = d = 5$.

In these equations, z_0 is a local characteristic constant and U, Θ, and q are given by the PERIDOT model at the lowest level in the air (nearly 20 m).

Equations (1), (3), and (5) allow us to determine surface temperature and humidity. It is now necessary to compute the output parameters by interpolation between the lowest level of the PERIDOT model (nearly 20 m) and the surface. This step is absolutely essential to compare observations with MUSCLES forecasts and to carry out the adjustment of local characteristic constants in order to minimize the corresponding forecast errors.

c. Interpolation to the height of measurements

The method used is operational in the PERIDOT model to interpolate wind, temperature, and humidity from the model levels to the height of measurements. Following Geleyn (1988), who supposed that the universal functions have the form $1 + \alpha_s z/\text{Lmo}$ in the stable case and $(1 - \alpha_i z/\text{Lmo})^{-1}$ in the unstable case, the following can be written.

Stable case:

$$U(z) = \frac{U(z_1)}{B_d}\left[A_n - \frac{z}{z_1}(B_n - B_d)\right]$$
$$\Theta(z) - \Theta_s = \frac{\Theta(z_1) - \Theta_s}{B_h}\left[A_n - \frac{z}{z_1}(B_n - B_h)\right] \quad (8)$$

Unstable case:

$$U(z) = \frac{U(z_1)}{B_d} \times \left\langle A_n - \ln\left\{1 + \frac{z}{z_1}[\exp(B_n - B_d) - 1]\right\}\right\rangle$$
$$\Theta(z) - \Theta_s = \frac{\Theta(z_1) - \Theta_s}{B_h} \times \left\langle A_n - \ln\left\{1 + \frac{z}{z_1}[\exp(B_n - B_h) - 1]\right\}\right\rangle \quad (9)$$

where $B_n = K_a/a$, $B_d = K_a(aF_u^{1/2})^{-1}$, $B_h = K_aF_u^{1/2} \times (aF_\Theta)^{-1}$, and $A_n = \ln[1 + (z/z_1)\exp(B_n - 1)]$.

The formulation for q is the same as for Θ.

d. MUSCLES validation

In order to validate the MUSCLES model, the evolution of the output parameters with the PERIDOT forcing was simulated for 1 year for the grid point nearest to the Le Bourget station, a meteorological station 10 km north of Paris.

The PERIDOT atmospheric forcing consists in imposing the forecasted values of the temperature, humidity, and wind at the lowest level in the air (nearly 20 m) every 3 h and by using a temporal linear interpolation of these data at each time step of the MUSCLES model (10′). The choice of the lowest level has been fixed due to the following reasons: it is very close to the PERIDOT modelization in order to compute checking experiments in good conditions and it is sure to be in the validity area of the laws of the surface boundary layer.

The PERIDOT soil forcing is made by imposing the deep soil temperature, the solar and thermic radiative fluxes, and the precipitation flux with the same method at each time step of the MUSCLES model, from 0000 UTC during 36 h of forecasting.

In this experiment, the local characteristic constants of the ground (ϵ, C_{soil}, z_0, desert, C_1, C_2, A) are chosen to be equal to those of the PERIDOT model for the grid point considered. In these conditions, the results obtained for 2-m temperature (T 2 m) and humidity (Q 2 m) and 10-m wind (FF 10 m) must be very close to the PERIDOT values because the differences between the two methods are primarily due to the time interpolation procedure.

For one year from September 1988 to August 1989, the mean absolute difference between the two methods is 0.1 K for the 2-m temperature, 0.00005 kg kg^{-1} for the 2-m specific humidity, and 0.05 m s^{-1} for the 10-m wind.

The results obtained are one order of magnitude lower than the signal being explained. Thus, the method is considered valid. It is now possible to address the problem of the adjustment of the local characteristic constants in order to minimize the forecast errors with a variational method using the adjoint of the MUSCLES model.

3. The variational method to adjust the local characteristic constants

Optimizing the local characteristic constants by using the variational technique consists in minimizing a cost function that measures the distance between observed values and their forecast equivalents. For an efficient implementation of such a method, it is necessary to determine the gradient of this cost function with respect to the seven local characteristic constants. In the language of optimal control, these constants form the control variable. This gradient can be determined practically using the adjoint of the MUSCLES model. All those techniques have been used in this study and will be explained in the following section.

a. Theory of the variational optimization

The first step is to choose the cost function. Two different sets of information are available for this use. First, observations measured at the meteorological station considered are removed. We define the observation error covariance matrix **O**, which corresponds to the incertitude given to the observations and to the forecasts made by MUSCLES; in fact, the matrix **O** includes the real measurement errors (0.2 K for T 2 m, 0.00009 kg kg^{-1} for Q 2 m, and 0.05 m s^{-1} for FF 10 m) and the computational errors inherent to the MUSCLES model (errors estimated throughout one year between the PERIDOT forecasts and the MUSCLES forecasts computed with the PERIDOT local characteristic constants).

Second, the set of local constants, which is chosen in PERIDOT, is known and is called the "first guess." Using our knowledge of the numerical models, a certain confidence is assigned to the first guess by means of the error covariance matrix **P** (Table 1).

It is very interesting to take into account the guess, as it allows an increase in the number of available pieces of information, and therefore the number of equations to solve, without an increase in the number of unknown factors. Thus, it makes the calculations of optimization more stable, which is the goal if the forecasts of the PERIDOT model are to be improved. Besides, taking into account the guess allows the use of a relaxation term toward the values of the PERIDOT local constants and an adjustment, by means of the matrix **P**, of the strength of this relaxation term. Therefore, it avoids obtaining local characteristic constants that would be too different of the PERIDOT ones and would not be physically realistic.

TABLE 1. Determination of the matrix **P** example of Le Bourget. This table presents the PERIDOT values of the local constants (first guess) and the standard deviation that has been chosen for determining the first-guess error variance–covariance matrix.

	PERIDOT values	Standard deviation
ϵ	0.96	0.01
C_{soil}	11×10^{-6}	10×10^{-6}
z_0	0.73	0.5
desert	0.3	0.25
C_1	20	12
C_2	0.2	0.12
A	0.12	0.04

Because of those different reasons, the following cost function has been chosen, which corresponds, in the case where the model is linear, to the variational formula of optimal interpolation (Jazwinski 1970; Lorenc 1988),

$$J(X) = J_{\text{guess}} + J_{\text{obs}} = {}^t(X - \text{Xg})\mathbf{P}^{-1}(X - \text{Xg}) + {}^t(GX - \mathbf{Yo})\mathbf{O}^{-1}(GX - \mathbf{Yo}), \quad (10)$$

where X is the control variable containing the local characteristic constants that are related to $\mathbf{Y}$, the vector of the output parameters, by the following equation: $Y = GX$.

Here Xg is a first guess for X; its value is taken equal to the local characteristic constants used in the PERIDOT model; **Yo** is the vector containing the observations of the three meteorological parameters: T 2 m, Q 2 m, and FF 10 m, from 0300 UTC to 3600 UTC through a 3-h time step (in all, 36 observations); G denotes the MUSCLES model that computes the output parameters; G' denotes the tangent linear operator of G; and **P** and **O** are, respectively, the first-guess error and the observation error covariance matrices.

The aim of the variational optimization is to find, by an iterative way, the set X of the local characteristic constants that minimizes the cost function, thanks to the knowledge of its gradient with respect to X. For this study, M1GC2, an algorithm based on an adaptative quasi-Newtonian technique, is used (provided by C. Lemarechal, INRIA). A description of this algorithm can be found in Buckley and Lenir (1983) and in Navon and Legler (1987). At each iteration, it requires the computation of the gradient of J with respect to X, which can be written with the cost function described previously:

$$\nabla_X J = \nabla_X J_{\text{guess}} + \nabla_X J_{\text{obs}}.$$

The gradient of J_{guess} with respect to X is easily calculated:

$$\nabla_X J_{\text{guess}} = 2\mathbf{P}^{-1}(X - \text{Xg}).$$

In order to compute $\nabla_X J_{\text{obs}}$, it is very practical to use the adjoint operator. Talagrand and Courtier (1987) have shown that $\nabla_X J = G'^* \nabla_Y J$, where G'^* is the adjoint of the tangent linear operator of G, and

$$\nabla_X J_{\text{obs}} = 2G'^*\mathbf{O}^{-1}(GX - \mathbf{Yo}).$$

Finally, the gradient of J with respect to X is written as follows:

$$\nabla_X J = 2\mathbf{P}^{-1}(X - \text{Xg}) + 2G'^*\mathbf{O}^{-1}(GX - \mathbf{Yo}). \quad (11)$$

In the minimization algorithm, there is an inner product that measures the distance between the approximate and the optimal solution. The choice of this inner product is generally based on physical or practical considerations. However, one must notice that the choice of the initial inner product is easily handled: the definition of a new gradient corresponding to a new inner product indeed leads to a simple matrix multiplication.

In order to improve the conditioning of the minimization problem and to speed up the convergence of the algorithm, it is very important to correctly choose this inner product. Looking at the analytical quadratic expression of the cost function, the ideal inner product denoted $\langle\ \rangle$ is associated to the matrix **H** of the second derivatives of the cost function, which is called the Hessian (Thépaut and Moll 1990),

$$\langle X, Y\rangle = {}^tX\mathbf{H}Y \quad \text{with} \quad \mathbf{H} = 2\mathbf{P}^{-1} + 2G'^*\mathbf{O}^{-1}G'. \quad (12)$$

This inner product transforms an elliptic problem into a spherical problem and thus defines the direction of descent without ambiguity. The gradient $\nabla_{\langle\ \rangle}$, with respect to the inner product $\langle\ \rangle$, is linked to the gradient ∇J used before by $\nabla_{\langle\ \rangle} = \mathbf{H}^{-1}\nabla J$. This is equivalent in the linear case to the first step of the minimization with a Newton algorithm (Gill et al. 1982).

b. The method's achievement

1) Validation of the linear tangent and adjoint of the MUSCLES model

The validation of the linear tangent model is achieved by verifying the Taylor expansion at the first order:

$$G(Z + h) - G(Z) = \langle\nabla_Z G, h\rangle + o(h).$$

The validation of the adjoint model is done according to two methods:

1) by directly using the fundamental definition of the adjoint $\forall(x, y) \in EXF$, $\langle Gx, y\rangle F = \langle x, G^*y\rangle E$, and

2) by using, as in Courtier (1987) and Thépaut and Courtier (1991), an indirect method that verifies the Taylor expansion at the first order. We consider h proportional to the gradient of J, that is, provided by the adjoint model.

Since the results are in agreement with the theory, the probability of an error in the gradient computation is very remote.

2) Projections of the cost function

Prior to using the minimization algorithm, it is worth checking that the cost function has no secondary minima. This is why we have drawn its term, "difference to the observations (J_{obs})," by projections in the different directions of the control variable. Six of the seven values of the control variable are fixed, in which case J_{obs} becomes a function of only one variable.

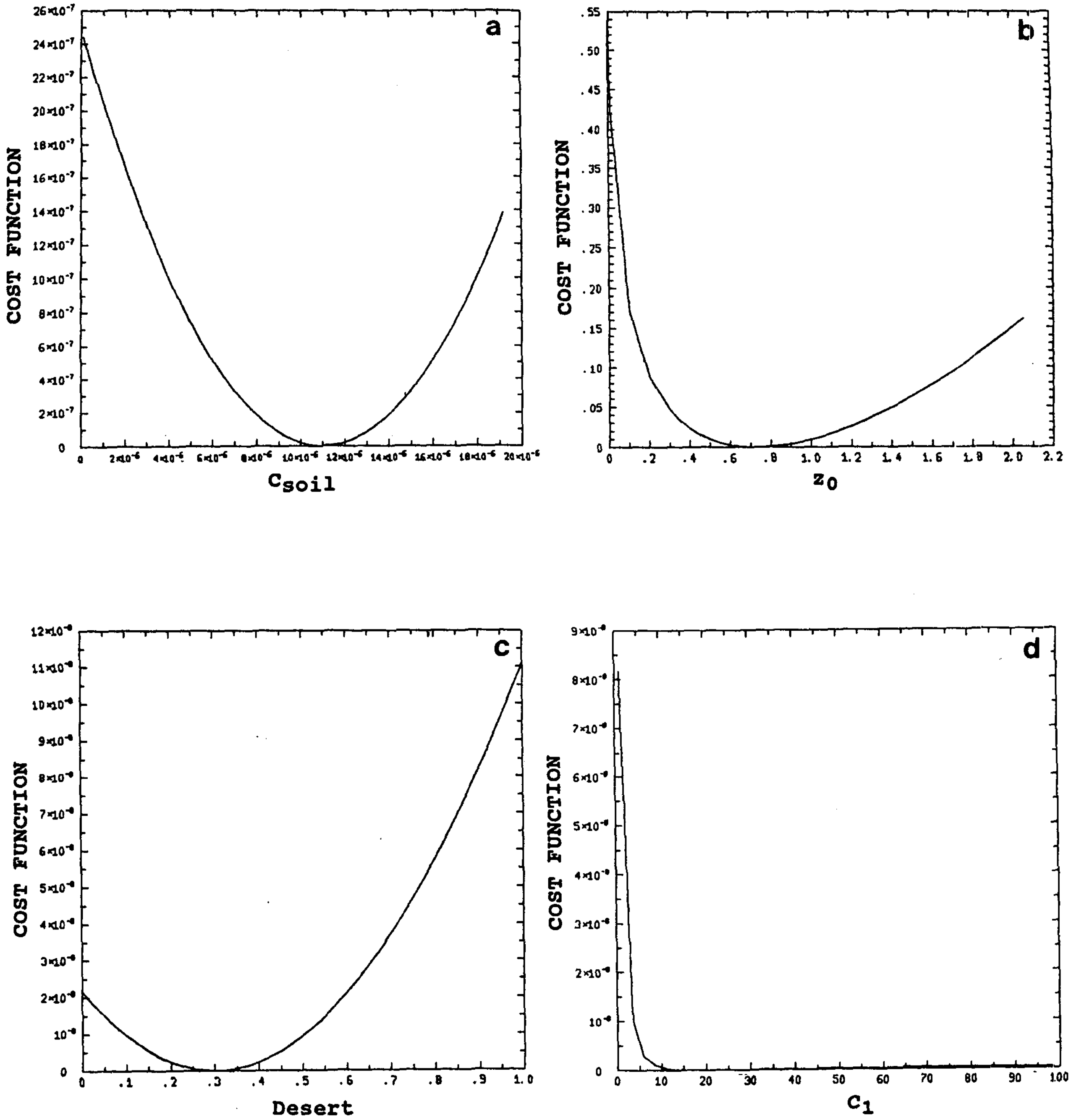


FIG. 1. Projections of the cost function for: (a) C_{soil}, (b) z_0, (c) desert, (d) C_1, (e) C_2, (f) A, and (g) ϵ.

In Figs. 1a–g, the diagrams for each value of the control variable are shown for the one day that is considered. The graduations on the x axis correspond to the values taken by the control variable and on the y axis to the J_{obs} values. These diagrams do not exhibit secondary minima in the variations' span of their parameters. Hence, the optimization experiments should be made in a very favorable numerical context.

3) Information content of the observed meteorological parameters

The variational formalism allows one to determine the quality of the information contained in the observed meteorological parameters in terms of local constants. This determination is done by examining the contribution of the meteorological parameters to

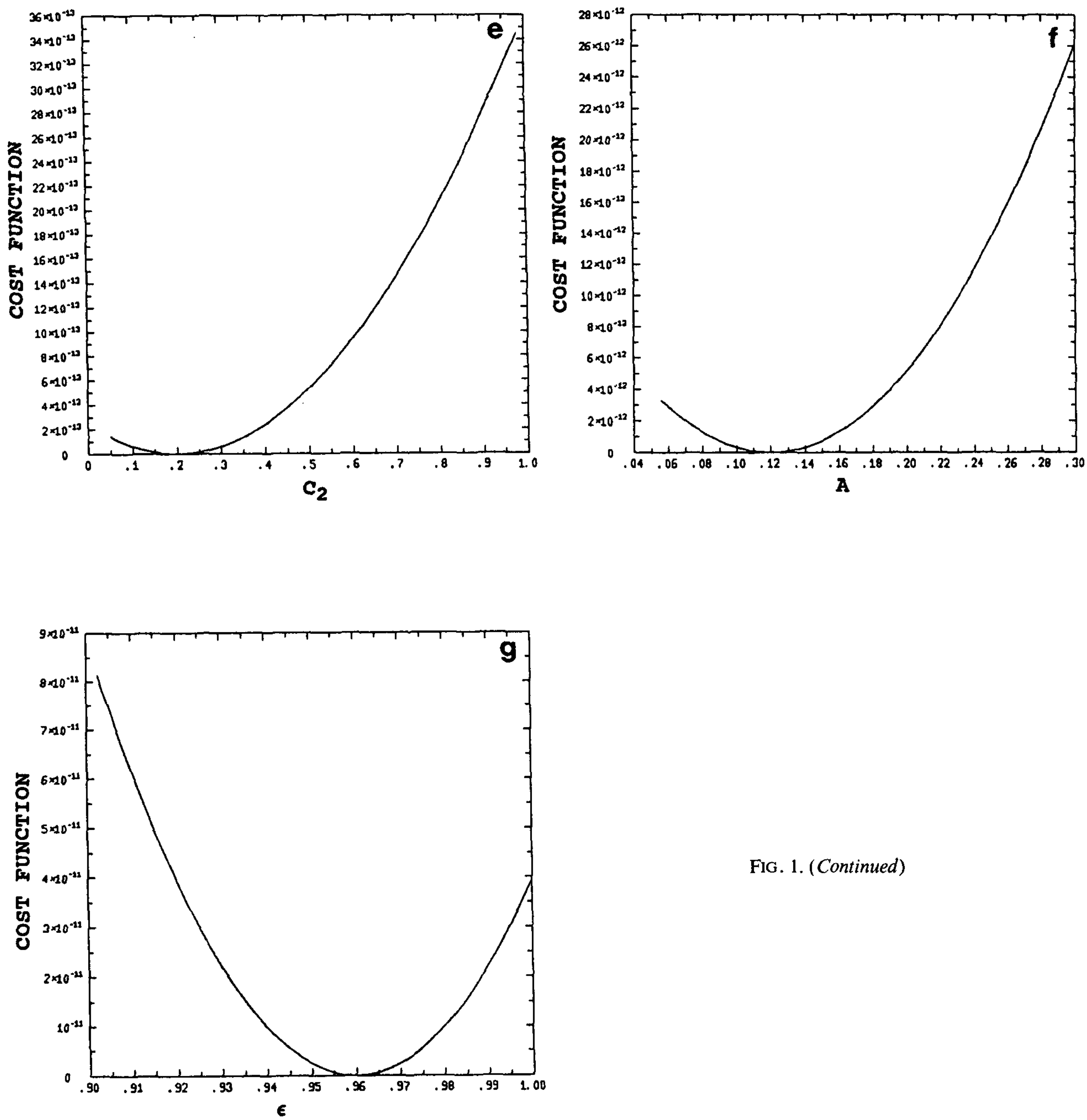


FIG. 1. (*Continued*)

the retrieval error covariance matrix of the local constants, that is, the matrix **B** defined by $\mathbf{B} = (G'\mathbf{O}^{-1}G')^{-1}$.

Thépaut and Moll (1990) have shown that the principal-component analysis (PCA) of the matrix $\mathbf{B}' = \mathbf{BP}^{-1}$ allows one to determine the gain brought by the observed meteorological parameters with respect to the guess: the smaller the eigenvalue, the more important the information coming from the observations.

Figures 2a–g present, for one considered day, the diagrams of the eigenvectors corresponding to the different eigenvalues. For the smallest eigenvalue (=2), the eigenvector gives information mainly on desert. For the second (=12), the eigenvector gives information on z_0; for the third (=60), C_1; and for the fourth (=167), C_{soil}. Above the fifth eigenvalue (=1915), there is no more information in the eigenvectors.

For other days of the period under consideration,

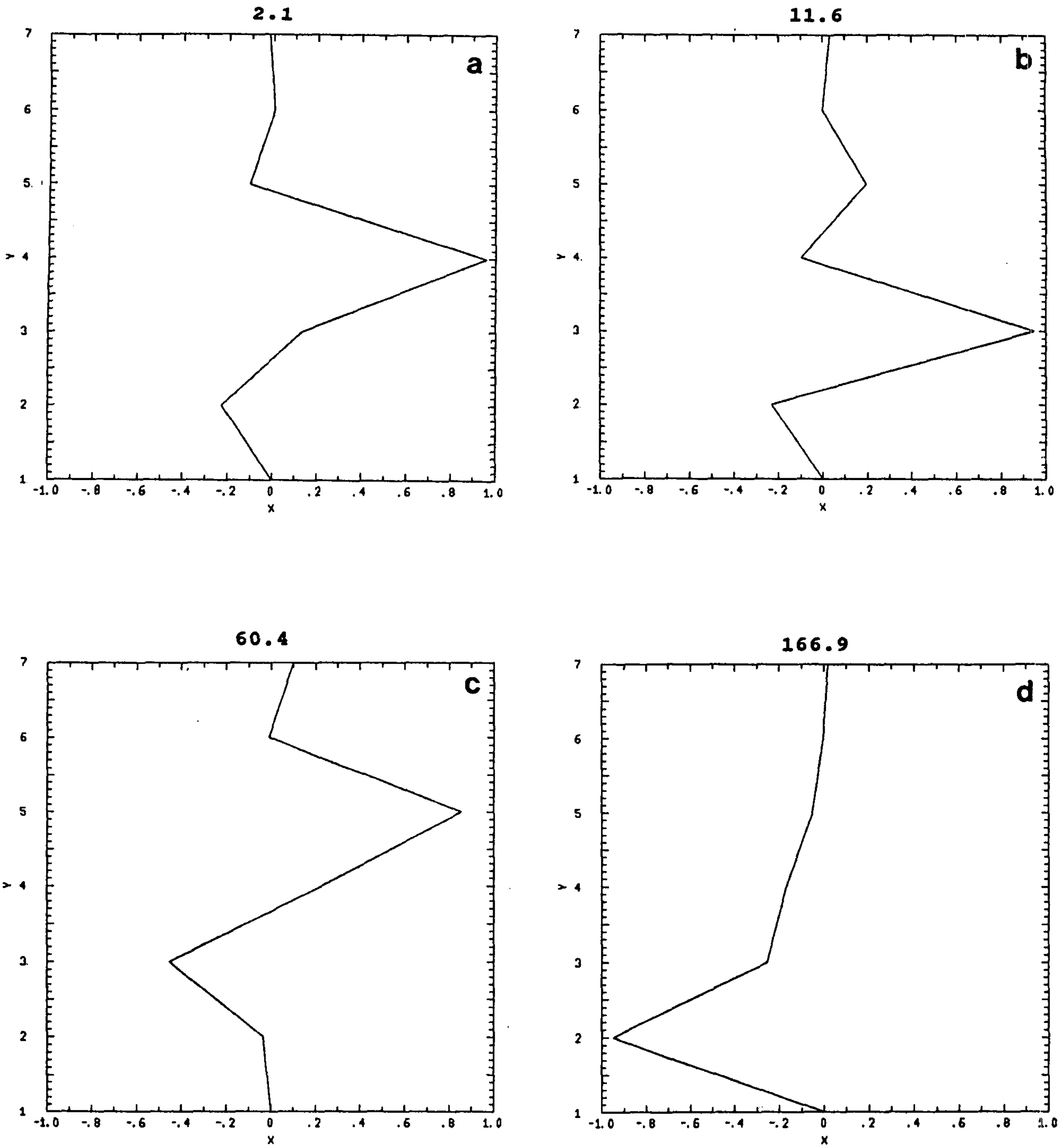


FIG. 2. Eigenvectors of the "observation term" of the retrieval-error covariance matrix. (a)–(g): the seven eigenvectors. At the top of each figure is the associated eigenvalue; X is the normalized amplitude of the eigenvector; Y represents the components of the eigenvector (1—ϵ; 2—C_{soil}; 3—z_0; 4—desert; 5—C_1; 6—C_2; 7—A).

desert, z_0, C_1, and C_{soil} are still the four significant independent pieces of information, even if they do not appear in the same order. The corresponding eigenvalues may be very different, which is why no conclusions about the variability of these constants are made.

In conclusion, from the seven local constants, there are in fact only four that are independent—desert, z_0, C_1, and C_{soil}—which are therefore the only ones that can be effectively determined.

With such an estimation, it would be possible, for

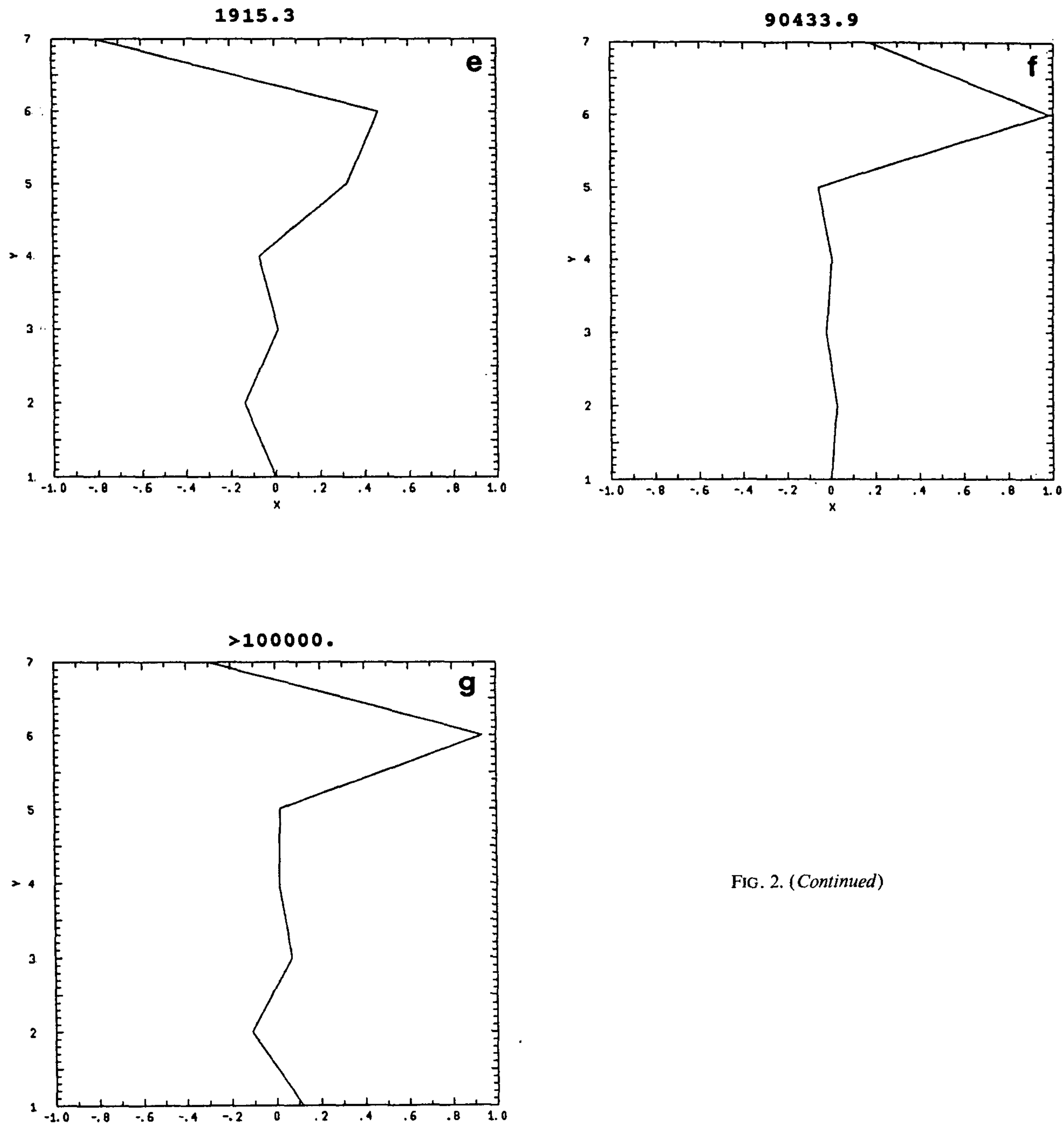


FIG. 2. (*Continued*)

operational use, to significantly reduce the number of local constants to be adjusted and thus gain computational time. However, for this study, the seven local characteristic constants that form the control variable are kept.

The method of variational optimization described in section 3b is now applied for several synoptic stations, and the gains obtained using this method are determined.

4. Results

a. Results of the variational optimization

First of all, we apply the method described above for Le Bourget throughout the year September 1988–August 1989.

Each day, the variational optimization method is applied and a control variable called Xm is obtained. The diagrams in Figs. 3a–g represent all the results

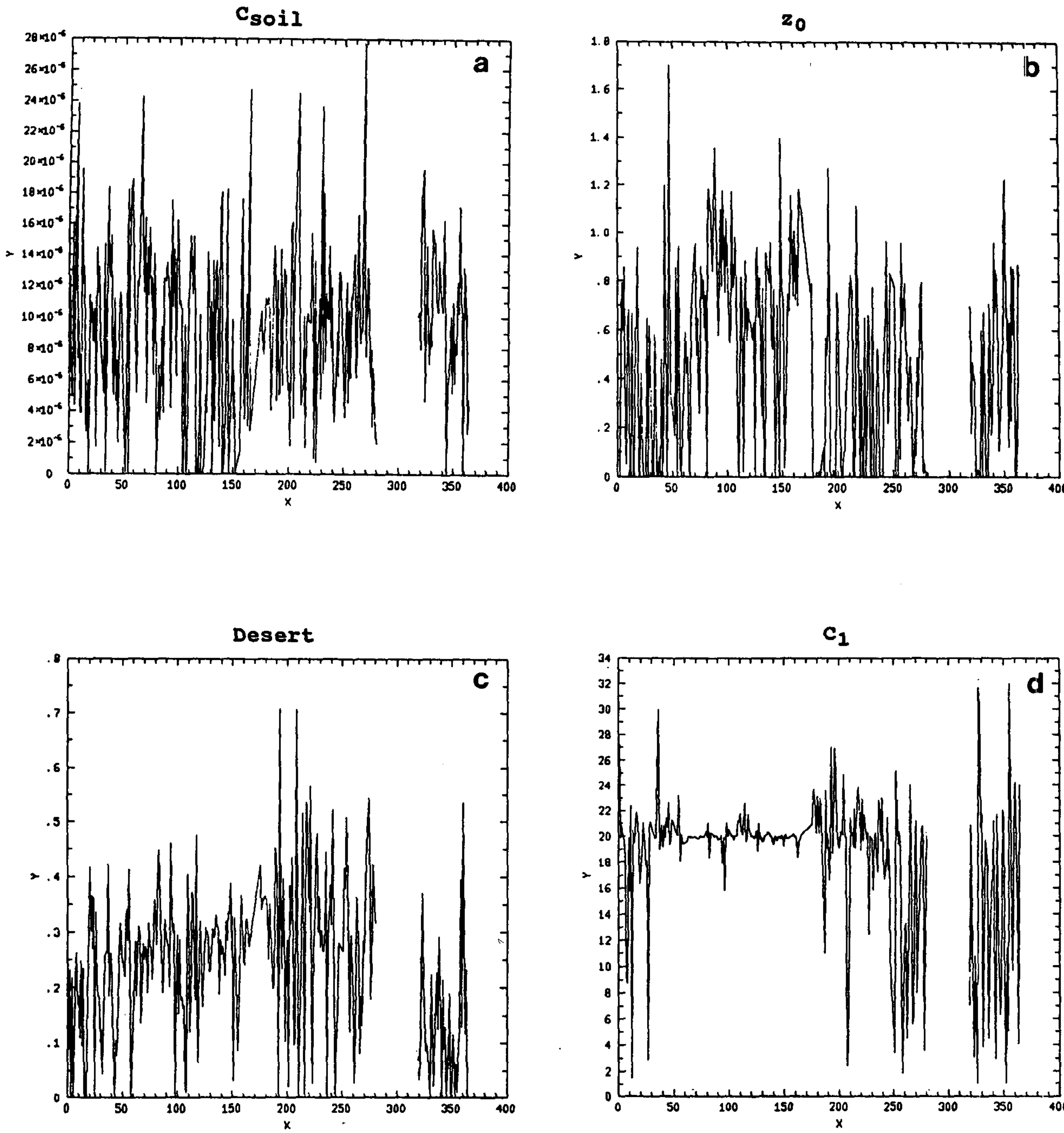
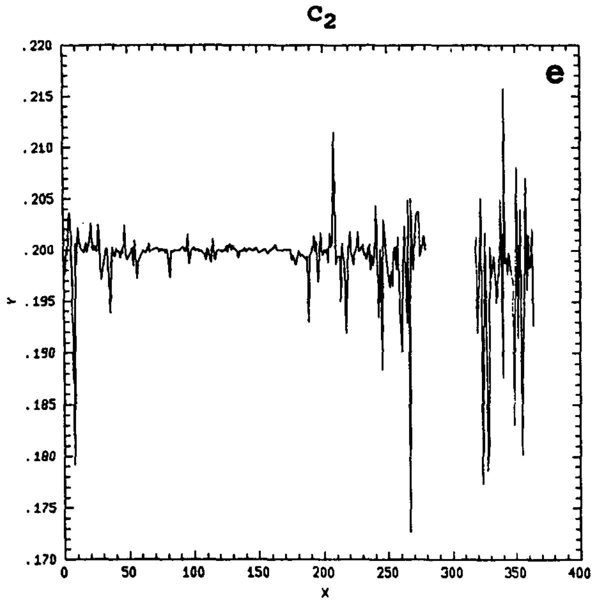
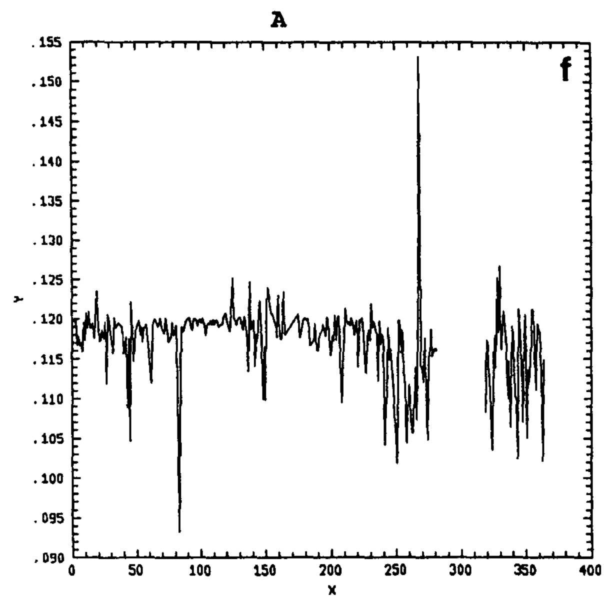


FIG. 3. Temporal variability of the local constants obtained by variational optimization: (a) C_{soil}, (b) z_0, (c) desert, (d) C_1, (e) C_2, (f) A, and (g) ϵ.

(there is a gap during July 1989 because the PERIDOT forecasts were not available during this period due to industrial action).

First we see that all these diagrams are characterized by an important scattering in time. This temporal variability is higher when the impact of the local constants on the forecast of the output parameters is more important. For example, the constants ϵ, C_2, and A (which is less informative) present a lower variability (their variations' span is very weak). This large temporal variability is likely to mean that the optimal adjustment of the local constants tries to correct the errors of the PERIDOT and MUSCLES models that are not directly linked to those constants.





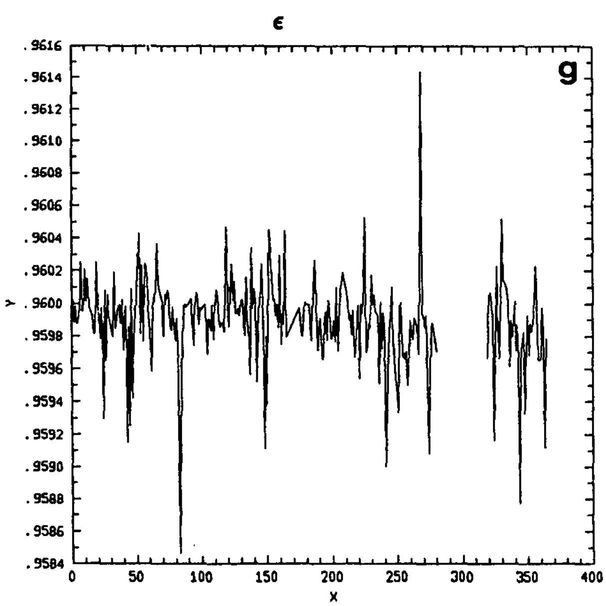


FIG. 3. (*Continued*)

Moreover, a well-marked seasonal variation for any local constant cannot be clearly distinguished. Consequently, these reasons will lead us to use running averages for the forecasting method.

Before considering the method of forecasting, it is first necessary to estimate the quality of the profiles that are retrieved using the control variable Xm obtained previously. That is, for each day of the period under consideration, new forecasts of the output parameters are determined by computing the MUSCLES model with this variable Xm. Then these forecasts are compared with the PERIDOT forecasts, and the gain obtained using this method is defined by substracting the MUSCLES error from the PERIDOT error. This gain represents the maximal gain that can be reached with such a method.

The results, in terms of gains in mean absolute error, are for the year 1989: 0.22 K for the 2-m temperature, 0.00012 kg kg^{-1} for the 2-m specific humidity, and 0.08 m s^{-1} for the 10-m wind speed.

The gain is rather important for both temperature and humidity but practically zero for the wind. This weak gain is understandable because only the direct effect of roughness is described in this method; the effects of wind adjustment to the orography are not taken into account here.

Because of these results, only the temperature is optimized by reducing the output parameters vector to this only scalar, especially since the requests of the potential users (particularly Electricité de France) are more urgent for this parameter. The gain for the temperature then becomes significantly higher (0.27 K), to the detriment of humidity and wind. On this subject, we can notice the adaptability of the method, which allows one to choose the variable or the set of variables to be optimized.

Subsequently, the optimization only for temperature is carried out on data from six French synoptic stations (Le Bourget, Brest, Lyon, Marignane, Strasbourg, and Toulouse) and for two periods of time: September 1988–August 1989 and the year 1990. These results are presented in Table 2. The highest gains are obtained for the stations where the errors of the PERIDOT model (Table 3) are most important (Lyon, Marignane, and Strasbourg), and the lowest gaines are obtained for the stations where the PERIDOT errors are less important (Le Bourget and Brest). Generally speaking, for all the considered stations, the quality of the gains is rather good.

TABLE 2. Variational optimization method for the six French stations and for years 1989 and 1990. The gains (MUSCLES error − PERIDOT error) are given in: MAE—mean absolute error, rms—root-mean-square, and std dev—standard deviation. The errors (in kelvins) are calculated every day from 0900 to 3600 UTC by steps of 3 h.

	MAE gain	rms gain	std dev gain
Le Bourget			
1989	0.27	0.30	0.26
1990	0.33	0.35	0.34
Brest			
1989	0.33	0.44	0.39
1990	0.30	0.39	0.37
Lyon			
1989	0.49	0.60	0.51
1990	0.51	0.57	0.52
Marignane			
1989	0.61	0.68	0.40
1990	0.78	0.85	0.57
Strasbourg			
1989	0.45	0.57	0.55
1990	0.43	0.48	0.46
Toulouse			
1989	0.42	0.49	0.39
1990	0.57	0.63	0.38

TABLE 3. Errors of PERIDOT forecasts of T 2 M for years 1989 and 1990. The PERIDOT errors are given in: MAE—mean absolute error, rms—root-mean-square, and std dev—standard deviation. The errors (in kelvins) are calculated every day from 0900 to 3600 UTC by steps of 3 h.

	MAE	rms	std dev
Le Bourget			
1989	1.87	2.36	2.20
1990	1.76	2.22	2.12
Brest			
1989	1.64	2.17	2.04
1990	1.46	2.00	1.93
Lyon			
1989	2.00	2.61	2.54
1990	1.96	2.55	2.49
Marignane			
1989	2.54	3.11	2.56
1990	2.38	3.00	2.57
Strasbourg			
1989	2.07	2.75	2.71
1990	1.83	2.40	2.37
Toulouse			
1989	2.00	2.58	2.37
1990	2.15	2.74	2.30

However, because of the extreme variability of the local constants, it is not evident at all that such good results can be obtained with an a priori forecasting method.

b. Results of the method in forecasting mode

Our first idea was to determine, season by season, a mean set of local constants, calculated from a learning file of one or several years. Following the important temporal variability (Figs. 3a–g), the lack of significant seasonal variation, and the differences in the signal from one year to another, it appeared better to consider the technique of running averages. In this case, the local constants are determined from the N days that precede the day d of the forecast. Another reason to use running averages instead of a single long-term average is that it seems more realistic to take into account the weather evolution on the previous days. In fact, this can have an influence on the adjustment of several local constants (for example snow for A and ϵ, rain for C_{soil}, C_1, and C_2). Besides, this technique seems to be more interesting since it avoids the heavy management of a learning file and it allows one to easily include the potential developments in the physics of the forcing numerical models.

Two different methods have been developed.

1) First method: each day, $J_i = J_{guess} + J_{obs\,i}$, $i = 1, N$ is computed and the optimization method is applied with J_i. Therefore, each day an optimized control variable X_i is obtained, which is called $\mathrm{Xm}^N = (1/N) \times \sum_{i=1}^{N} X_i$.

The MUSCLES model is computed with Xm^N as the control variable and forecasts from 0000 UTC to 3600 UTC are obtained, which are compared with the forecasts of PERIDOT.

2) Second method: J is computed on the N previous days, $J = J_{\text{guess}} + \sum_{i=1}^{N} J_{\text{obs}i}$, and the optimization method is applied with J. As in the former method, the Xm^N that is used is computed directly as the control variable for computing the MUSCLES model.

For the first method, different calculations have shown that the bests scores are obtained after about 10 days. For the second method, the best results are obtained after 20 days. Yet, because of the high computational cost, $N = 10$ is considered for the two methods, and therefore the results are presented for $N = 10$.

The results concerning the two methods are presented in Table 4 for 1989 and in Table 5 for 1990. The results for 1990 can be compared with the ones forecasted by statistical adaptation (Table 5); but this does not work for the results for 1989 because that year corresponds to the learning file of the statistical adaptation.

By the analysis of these tables, several conclusions can be drawn.

1) For all six stations, the second method clearly gives better results than the first one. This can be explained by the largest number of degrees of freedom, as the number of observations being used in J varies from 12 to 12N. Even if there is a higher computational cost, only this method is considered in the following text.

2) The lowest gain is obtained for Le Bourget, as in the optimization method. The nearest PERIDOT grid point of Le Bourget is not, perhaps, the "best point" for this method. For the other stations, the classification by score is different according to whether one looks at the mean absolute error, at the root-mean-square, or at the standard deviation. This last parameter is more selective because it takes off the bias.

3) For 1989, except for Le Bourget, the gains are of rather good quality, especially for Strasbourg, Lyon, and Brest. Unfortunately, they cannot be compared with the statistical gains.

4) The gains for 1990 are higher than those for 1989 for Marignane and Toulouse but lower for the other four towns. The scores for Le Bourget are significantly lower than the gains of statistical adaptation. For Marignane, Strasbourg, and Toulouse, the gains are divided in half, with respect to the ones of the statistical adaptation. For Brest and Lyon, the gains are nearly equal to that of the statistical adaptation.

TABLE 4. Application of the method in forecasting mode for the six French stations and for year 1989. The results are given for the two methods of forecast: 1) first method—J is computed on 1 day and 2) second method—J is computed on 10 days. The gains (MUSCLES error − PERIDOT error) are given in MAE—mean absolute error, rms—root-mean-square, and std dev—standard deviation. The errors (in kelvins) are calculated every day from 0900 to 3600 UTC by steps of 3 h.

	MAE gain	rms gain	std dev gain
Le Bourget			
1)	0.05	0.05	0.03
2)	0.10	0.10	0.05
Brest			
1)	0.13	0.19	0.12
2)	0.23	0.32	0.20
Lyon			
1)	0.17	0.25	0.17
2)	0.24	0.33	0.22
Marignane			
1)	0.32	0.34	0.09
2)	0.42	0.48	0.10
Strasbourg			
1)	0.16	0.24	0.22
2)	0.21	0.30	0.27
Toulouse			
1)	0.13	0.17	0.08
2)	0.21	0.24	0.12

TABLE 5. Application of the method in forecasting mode for the six French stations and for year 1990. The results are given for the two methods of forecast and for the statistical-adaptation method: 1) first method—J is computed on 1 day, 2) second method—J is computed on 10 days, and 3) statistical-adaptation method. The gains (MUSCLES error − PERIDOT error) are given in MAE—mean absolute error, rms—root-mean-square, and std dev—standard deviation. The errors (in kelvins) are calculated every day from 0900 to 3600 UTC by steps of 3 h.

	MAE gain	rms gain	std dev gain
Le Bourget			
1)	0.04	0.03	0.02
2)	0.06	0.06	0.03
3)	0.34	0.42	0.33
Brest			
1)	0.06	0.09	0.06
2)	0.10	0.15	0.11
3)	0.11	0.21	0.14
Lyon			
1)	0.12	0.15	0.10
2)	0.17	0.21	0.15
3)	0.21	0.28	0.24
Marignane			
1)	0.40	0.45	0.20
2)	0.51	0.56	0.24
3)	0.75	0.92	0.56
Strasbourg			
1)	0.09	0.12	0.10
2)	0.10	0.14	0.12
3)	0.24	0.33	0.31
Toulouse			
1)	0.23	0.27	0.09
2)	0.33	0.40	0.10
3)	0.51	0.63	0.21

5. Conclusions

This paper has presented the preliminary results of a local dynamical-interpretation method in the surface boundary layer. The purpose of this method is to adjust the local characteristic constants by using the variational technique. Although the local constants, obtained using this technique, are characterized by a great day-to-day variability, the first results seem to be promising. For all the considered stations except for Le Bourget, the quality of the gains is significant, even if they are lower than that of the statistical-adaptation technique.

In order to carry out a local temperature forecast (even of humidity or wind), this method has several advantages. First, the method is simple and can be easily applied to any station as long as there are measures of temperature (humidity or wind) and forecasts of a forcing model near the station (in France, the PERIDOT model) over the ten previous days. In addition, this method does not require the use of a learning file. Thus, it can be easily transported and adjusted to the evolutions of the physics in the forcing model.

The operational implications are important, since there is a high demand for local temperature forecasts (and even of humidity), especially in the fields of agriculture (forecast of frost for the crops) or energy (forecast of electricity or gas consumption).

In the future, several improvements could be made to this model. Because of the great daily variability of the local constants, we could try to select the situations where the PERIDOT error is coming more from a synoptical origin than from a local one. However, as a first step, this approach has seemed too difficult to be developed operationally (it is not so simple to determine the choice of the test). Nevertheless, this approach could perhaps lead to better results.

At present, the forcing of the model is chosen by using the nearest PERIDOT grid point of the station under consideration. This could be changed by using either the "best grid point" or an average on several grid points, which could be a function of the spatial structure of the PERIDOT errors.

At present, the PERIDOT atmospheric forcing consists in taking the PERIDOT values at the lowest level in the air (nearly 20 m). It would be very interesting to take into account the parameters at the second level (nearly 95 m) instead of the first one, or at a level interpolated between the two, because these values are less dependent on the soil conditions than the values at 20 m.

However, the most promising approach seems to try to add the gains of dynamical and statistical adaptations. The correlation between the statistical adaptation − PERIDOT and MUSCLES − PERIDOT errors (from 0900 to 3600 UTC by step of 3 h) is indeed rather weak (correlation coefficient equal to .3 for Le Bourget and Lyon; .4 for Brest, Strasbourg, and Toulouse; .5 for Marignane), which means that the statistical-adaptation method does not correct exactly the same errors as the MUSCLES model.

One of the reasons of the success of the statistical adaptation is the discovery of the best operator of spatial average for all the stations: it is a principal-component analysis (PCA) of the T 2 m field, the PERIDOT field being more informative at a scale of three or four times the grid mesh. For our study, the same argument would result in the introduction of a PERIDOT forcing computed by PCA. Of course, it would be necessary to verify that the gain obtained by adding dynamical and statistical methods is higher than the one found by each method separately, and this is not positive.

Finally, another potential use of the method presented here would be to improve the scores of the PERIDOT forecasts. It would consist in determining the optimal set of local characteristic constants to put in the operational code of PERIDOT for each grid point by optimization using the measures of the surrounding stations.

Acknowledgments. We wish to thank Patrick Moll for his valuable teaching of the variational technique and for his suggestions during that step. We acknowledge helpful and stimulating discussions with Jean-François Geleyn. Our thanks to Jean-Pierre Javelle for his useful comments and to Philippe Courtier for comments and for checking the manuscript. We wish also to thank the two reviewers for their pertinent comments, which improved our paper. This work was partially supported by Electricité de France.

REFERENCES

Bhumralkar, C. M., 1975: Numerical experiments on the computation of ground surface temperature in an atmospheric general circulation model. *J. Appl. Meteor.*, **14**, 1246–1258.

Buckley, A. A., and A. Lenir, 1983: *QN*-like variable storage conjugate gradient. *Math. Program.*, **27**, 155–175.

Burk, S. D., and W. Thompson, 1982: Operational evaluation of a temperature closure model forecast system. *Mon. Wea. Rev.*, **11**, 1535–1543.

Coiffier, J., Y. Ernie, J. F. Geleyn, J. Clochard, J. Hoffman, and F. Dupont, 1987: The Operational Hemispheric Model at the French Meteorological Service. *J.M.S.J., Special NWP Symp.*, Tokyo, 337–345.

Courtier, P., 1987: Application du contrôle optimal à la prévision numérique en Météorologie. Doctoral thesis, University of Paris.

Deardorff, J. W., 1978: Efficient prediction of ground surface temperature and moisture with inclusion of a layer of vegetation. *J. Geophys. Sci.*, **63**, 1889–1903.

Geleyn, J. F., 1988: Interpolation of wind, temperature and humidity from model levels to the height of measurement. *Tellus*, **40A**, 347–351.

Gill, P. E., W. Murray, and M. H. Wright, 1982: *Practical Optimization.* Academic Press.

Jazwinski, A. H., 1970: *Stochastic Processes and Filtering Theory.* Academic Press.

Juvanon Du Vachat, R., J. M. Audoin, M. Imbard, L. Musson-Genon, and J. P. Javelle, 1988: Evaluation of a mesoscale prediction system with surface weather observations and comparison with a large scale prediction system. *Proc. Symp. on Mesoscale Analysis and Forecasting,* Vancouver.

Lorenc, A. C., 1988: Optimal non-linear objective analysis. *Quart. J. Roy. Meteor. Soc.,* **114,** 205–240.

Louis, J. F., 1979: A parametric model of vertical eddy fluxes in the atmosphere. *Bound.-Layer Meteor.,* **17,** 187–202.

——, M. Tiedke, and J. F. Geleyn, 1982: A short history of the PBL parameterization at ECMWF. *Proc. ECMWF Workshop on Planetary Boundary Layer Parameterization,* 59–79.

Musson-Genon, L., 1989: Forecasting in the vertical with a local dynamical interpretation method. *Mon. Wea. Rev.,* **117,** 29–39.

Navon, I. M., and D. M. Legler, 1987: Conjugate-gradient methods for large-scale minimization in meteorology. *Mon. Wea. Rev.,* **115,** 1479–1502.

Pottier, P., 1991: Utilisation de l'analyse en composantes principales pour la prévision statistique en météorologie. *Rev. Stat. Appl.,* **39**(1), 37–49.

——, G. Der Mégréditchian, and J. P. Javelle, 1989: Application of statistical methods to operational forecasts in France. *Proc. 11th Conf. on Probability and Statistics,* Amer. Meteor. Soc., 98–102.

Reiff, J., D. Blauboer, H. A. R. De Bruin, A. P. Van Ulden, and G. Cats, 1984: An air mass transformation model for short-range weather forecasting. *Mon. Wea. Rev.,* **112,** 393–412.

Talagrand, O., and P. Courtier, 1987: Variational assimilation of meteorological observations with the adjoint vorticity equation. Part I, theory. *Quart. J. Roy. Meteor. Soc.,* **113,** 1313–1330.

Thépaut, J. N., and P. Moll, 1990: Variational inversion of simulated TOVS radiances using the adjoint technique. *Quart. J. Roy. Meteor. Soc.,* **116,** 1425–1448.

——, and P. Courtier, 1991: Four dimensional variational data assimilation using the adjoint of a multilevel primitive equation model. *Quart. J. Roy. Meteor. Soc.*