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Modélisation Numérique de l'Écoulement Atmosphérique et Assimilation d'Observations

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Best Linear Unbiased Estimate

State vector x, belonging to *state space* $\mathcal{S}$ ($\dim \mathcal{S} = n$), to be estimated.

Available data in the form of

- A '*background*' estimate (*e. g.* forecast from the past), belonging to *state space*, with dimension n

  $$x^b = x + \zeta^b$$

- An additional set of data (*e. g.* observations), belonging to *observation space*, with dimension p

  $$y = Hx + \varepsilon$$

  H is known linear *observation operator*.

Assume probability distribution is known for the couple (ζ^b, ε).

Assume $E(\zeta^b) = 0$, $E(\varepsilon) = 0$, $E(\zeta^b \varepsilon^T) = 0$ (not restrictive)

Set $E(\zeta^b \zeta^{bT}) = P^b$ (also often denoted B), $E(\varepsilon\varepsilon^T) = R$

Best Linear Unbiased Estimate (continuation 1)

$$\boldsymbol{x}^b = \boldsymbol{x} + \boldsymbol{\zeta}^b \qquad (1)$$

$$\boldsymbol{y} = H\boldsymbol{x} + \boldsymbol{\varepsilon} \qquad (2)$$

A probability distribution being known for the couple $(\boldsymbol{\zeta}^b, \boldsymbol{\varepsilon})$, eqs (1-2) define probability distribution for the couple $(\boldsymbol{x}, \boldsymbol{y})$, with

$$E(\boldsymbol{x}) = \boldsymbol{x}^b \,, \;\; \boldsymbol{x}' = \boldsymbol{x} - E(\boldsymbol{x}) = -\,\boldsymbol{\zeta}^b$$

$$E(\boldsymbol{y}) = H\boldsymbol{x}^b \,, \;\; \boldsymbol{y}' = \boldsymbol{y} - E(\boldsymbol{y}) = \boldsymbol{y} - H\boldsymbol{x}^b = \boldsymbol{\varepsilon} - H\boldsymbol{\zeta}^b$$

$\boldsymbol{d} \equiv \boldsymbol{y} - H\boldsymbol{x}^b$ is called the *innovation vector*.

Best Linear Unbiased Estimate (continuation 2)

Apply formulæ for Optimal Interpolation

$$\mathbf{x}^a = \mathbf{x}^b + P^b H^T [HP^bH^T + R]^{-1} (\mathbf{y} - H\mathbf{x}^b)$$
$$P^a = P^b - P^b H^T [HP^bH^T + R]^{-1} HP^b$$

x^a is the *Best Linear Unbiased Estimate* (*BLUE*) of x from x^b and y.

Equivalent set of formulæ

$$\mathbf{x}^a = \mathbf{x}^b + P^a H^T R^{-1} (\mathbf{y} - H\mathbf{x}^b)$$
$$[P^a]^{-1} = [P^b]^{-1} + H^T R^{-1} H$$

Matrix $K = P^b H^T [HP^bH^T + R]^{-1} = P^a H^T R^{-1}$ is *gain matrix*.

If probability distributions are *globally* gaussian, *BLUE* achieves bayesian estimation, in the sense that $P(\mathbf{x} \mid \mathbf{x}^b, \mathbf{y}) = \mathcal{N}[\mathbf{x}^a, \mathbf{P}^a]$.

Best Linear Unbiased Estimate (continuation 3)

H can be any linear operator

Example : (scalar) satellite observation

$$\boldsymbol{x} = (x_1, \ldots, x_n)^T \text{ temperature profile}$$

Observation $\quad y = \Sigma_i h_i x_i + \varepsilon = \boldsymbol{H}\boldsymbol{x} + \varepsilon \quad , \quad \boldsymbol{H} = (h_1, \ldots, h_n) \quad , \quad E(\varepsilon^2) = r$

Background $\quad \boldsymbol{x}^b = (x_1{}^b, \ldots, x_n{}^b)^T \quad ,$ error covariance matrix $P^b = (p_{ij}{}^b)$

$$\boldsymbol{x}^a = \boldsymbol{x}^b + P^b H^T [HP^bH^T + R]^{-1} (\boldsymbol{y} - H\boldsymbol{x}^b)$$

$[HP^bH^T + R]^{-1} (\boldsymbol{y} - H\boldsymbol{x}^b) = (y - \Sigma_\iota h_\iota x_\iota{}^b) / (\Sigma_{ij} h_i h_j p_{ij}{}^b + r)^{-1} \equiv \mu$ scalar !

- $P^b = p^b \boldsymbol{I}_n \qquad x_i^a = x_i^b + p^b h_i \mu$
- $P^b = \mathrm{diag}(p_{ii}{}^b) \qquad x_i^a = x_i^b + p_{ii}{}^b h_i \mu$
- General case $\qquad x_i^a = x_i^b + \Sigma_j p_{ij}{}^b h_j \mu$

Each level i is corrected, not only because of its own contribution to the observation, but because of the contribution of the other levels to which its background error is correlated.

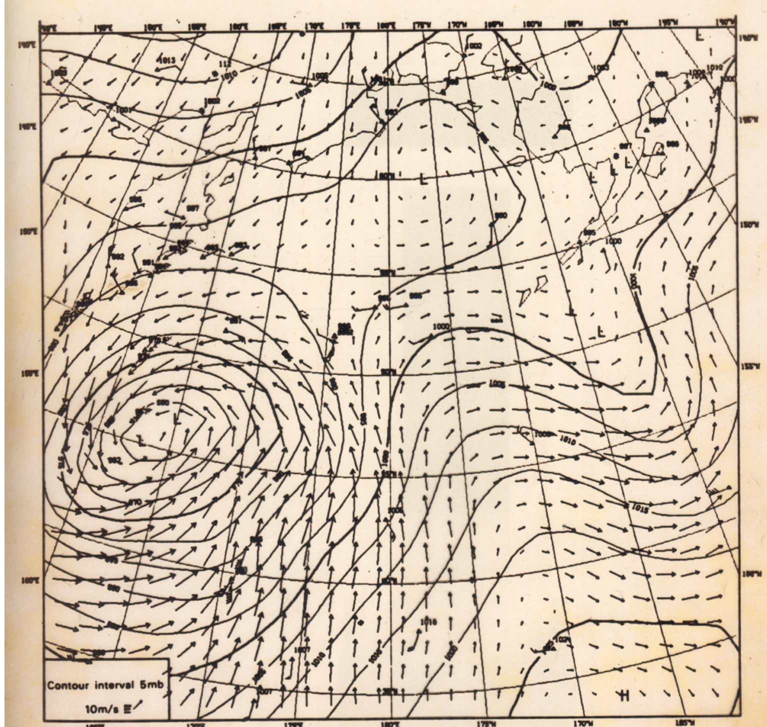


Fig. 4 Sea level pressure and wind forecast corresponding to the central area of Fig. 1, with plotted surface observations of pressure and wind (each fleche = 5 m/s).

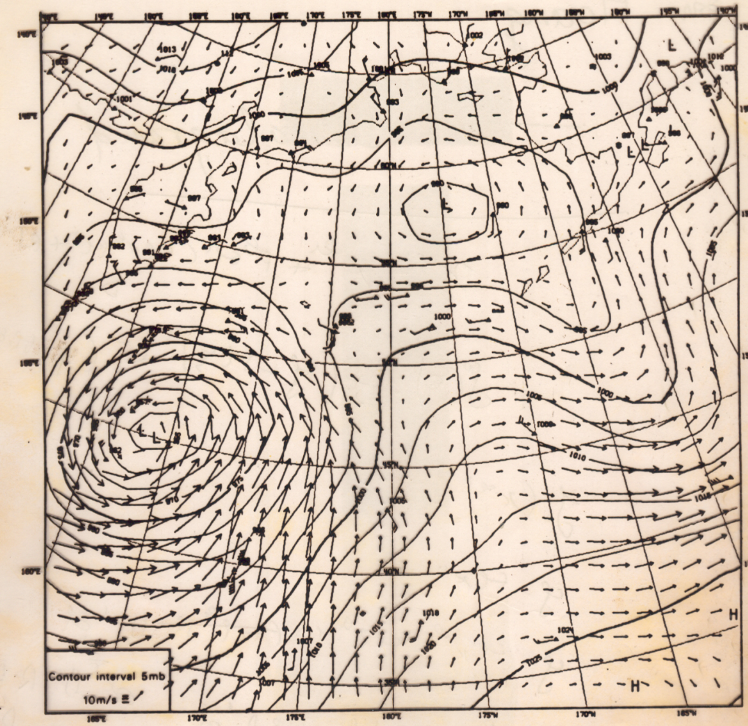


Fig. 5 As Fig. 4 for the analysis in the data assimilation cycle

After A. Lorenc

Best Linear Unbiased Estimate (continuation 4)

Variational form of the *BLUE*

BLUE x^a minimizes following scalar *objective function*, defined on state space

$\xi \in \mathcal{S} \rightarrow$

$$\mathcal{J}(\xi) = (1/2)\,(x^b - \xi)^{\mathrm{T}}\,[P^b]^{-1}\,(x^b - \xi) + (1/2)\,(y - H\xi)^{\mathrm{T}}\,R^{-1}\,(y - H\xi)$$

$$= \mathcal{J}_b + \mathcal{J}_o$$

'*3D-Var*'

Can easily, and heuristically, be extended to the case of a nonlinear observation operator H.

Used operationally in USA, Australia, China, …

Question. How to introduce temporal dimension in estimation process ?

- Logic of Optimal Interpolation can be extended to time dimension.

- But we know much more than just temporal correlations. We know explicit dynamics.

Real (unknown) state vector at time k (in format of assimilating model) x_k. Belongs to state space $\mathcal{S}$ ($\dim \mathcal{S} = n$)

Evolution equation

$$x_{k+1} = M_k(x_k) + \eta_k$$

M_k is (known) model, η_k is (unknown) model error

Sequential Assimilation

- Assimilating model is integrated over period of time over which observations are available. Whenever model time reaches an instant at which observations are available, state predicted by the model is updated with new observations.

Variational Assimilation

- Assimilating model is globally adjusted to observations distributed over observation period. Achieved by minimization of an appropriate scalar *objective function* measuring misfit between data and sequence of model states to be estimated.

- Observation vector at time k

$$y_k = H_k x_k + \varepsilon_k \qquad\qquad k = 0, \ldots, K$$

$$E(\varepsilon_k) = 0 \quad ; \quad E(\varepsilon_k \varepsilon_j^{\mathrm{T}}) = R_k \, \delta_{kj}$$

H_k linear

- Evolution equation

$$x_{k+1} = M_k x_k + \eta_k \qquad\qquad k = 0, \ldots, K\text{-}1$$

$$E(\eta_k) = 0 \quad ; \quad E(\eta_k \eta_j^{\mathrm{T}}) = Q_k \, \delta_{kj}$$

M_k linear

- $E(\eta_k \varepsilon_j^{\mathrm{T}}) = 0$ (errors uncorrelated in time)

At time k, background $x^b{}_k$ and associated error covariance matrix $P^b{}_k$ known

- Analysis step

$$x^a{}_k = x^b{}_k + P^b{}_k H_k{}^T [H_k P^b{}_k H_k{}^T + R_k]^{-1} (y_k - H_k x^b{}_k)$$
$$P^a{}_k = P^b{}_k - P^b{}_k H_k{}^T [H_k P^b{}_k H_k{}^T + R_k]^{-1} H_k P^b{}_k$$

- Forecast step

$$x^b{}_{k+1} = M_k x^a{}_k$$
$$\begin{aligned} P^b{}_{k+1} &= E[(x^b{}_{k+1} - x_{k+1})(x^b{}_{k+1} - x_{k+1})^T] = E[(M_k x^a{}_k - M_k x_k - \eta_k)(M_k x^a{}_k - M_k x_k - \eta_k)^T] \\ &= M_k E[(x^a{}_k - x_k)(x^a{}_k - x_k)^T] M_k{}^T - E[\eta_k (x^a{}_k - x_k)^T] - E[(x^a{}_k - x_k)\eta_k{}^T] + E[\eta_k \eta_k{}^T] \\ &= M_k P^a{}_k M_k{}^T + Q_k \end{aligned}$$

At time k, background $x^b{}_k$ and associated error covariance matrix $P^b{}_k$ known

- Analysis step

$$x^a{}_k = x^b{}_k + P^b{}_k H_k{}^T [H_k P^b{}_k H_k{}^T + R_k]^{-1} (y_k - H_k x^b{}_k)$$
$$P^a{}_k = P^b{}_k - P^b{}_k H_k{}^T [H_k P^b{}_k H_k{}^T + R_k]^{-1} H_k P^b{}_k$$

- Forecast step

$$x^b{}_{k+1} = M_k x^a{}_k$$
$$P^b{}_{k+1} = M_k P^a{}_k M_k{}^T + Q_k$$

Kalman filter (KF, Kalman, 1960)

Must be started from some initial estimate $(x^b{}_0, P^b{}_0)$

If all operators are linear, and if errors are uncorrelated in time, Kalman filter produces at time k the *BLUE* ${x^b}_k$ (resp. ${x^a}_k$) of the real state x_k from all data prior to (resp. up to) time k, plus the associated estimation error covariance matrix ${P^b}_k$ (resp. ${P^a}_k$).

If in addition errors are gaussian, the corresponding conditional probability distributions are the respective gaussian distributions

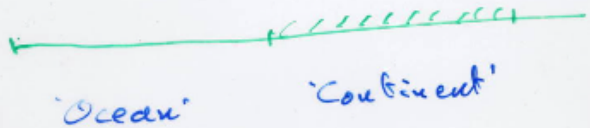
$\mathcal{N}[{x^b}_k, {P^b}_k]$ and $\mathcal{N}[{x^a}_k, {P^a}_k]$.

A didactic example (Ghil et al.)

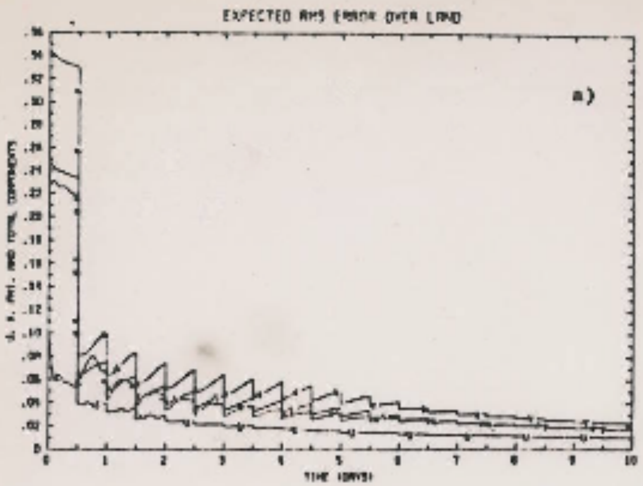
Barotropic model

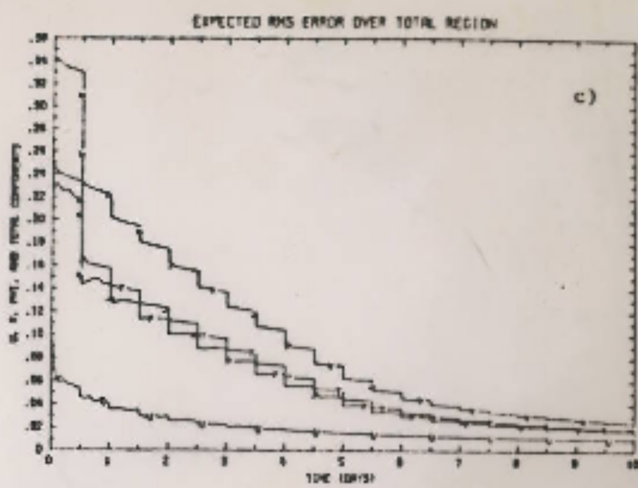
$$\begin{cases} \dfrac{\partial \varphi}{\partial t} + \operatorname{div}(\varphi \underline{U}) = 0 \\[2ex] \dfrac{\partial \underline{U}}{\partial t} + \underline{\operatorname{grad}}(\varphi + \frac{1}{2} U^2) + \underline{k} \times (f + \xi) \underline{U} = 0 \end{cases}$$

One dimension, periodic



Linearized (conserves energy)





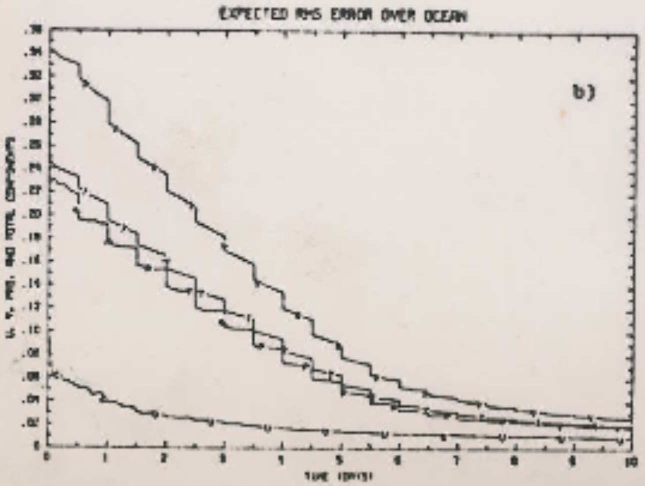


Fig. 2

The components of the total expected rms error (Erms), (trace: $P_k)^{1/2}$, in the estimation of solutions to the stochastic-dynamic system (Ψ,H), with Ψ given by (3.6) and H = (I 0). System noise is absent, Q = 0. The filter used is the standard K-B filter (2.11) for the model.

a) Erms over land; b) Erms over the ocean; c) Erms over the entire L-domain

In each one of the figures, each curve represents one component of the total Erms error. The curves labelled U, V, and P represent the u component, v component and ϕ component, respectively. They are found by summing the diagonal elements of P_k which correspond to u, v, and ϕ, respectively, dividing by the number of terms in the sum, and then taking the square root. In a) the summation extends over land points only, in b) over ocean points only, and in c) over the entire L-domain. The vertical axis is scaled in such a way that 1.0 corresponds to an Erms error of v_{max} for the U and V curves, and of ϕ_0 for the P curve. The observational error level is 0.089 for the U and V curves, and 0.080 for the P curve. The curves labelled T represent the total Erms error over each region. Each T curve is a weighted average of the corresponding U, V, and P curves, with the weights chosen in such a way that the T curve measures the error in the total energy $u^2 + v^2 + \phi^2/\bar{\phi}$, conserved by the system (3.1). The observational noise level for the T curve is then 0.088. Notice the immediate error decrease over land and the gradual decrease over the ocean. The total estimation error tends to zero.

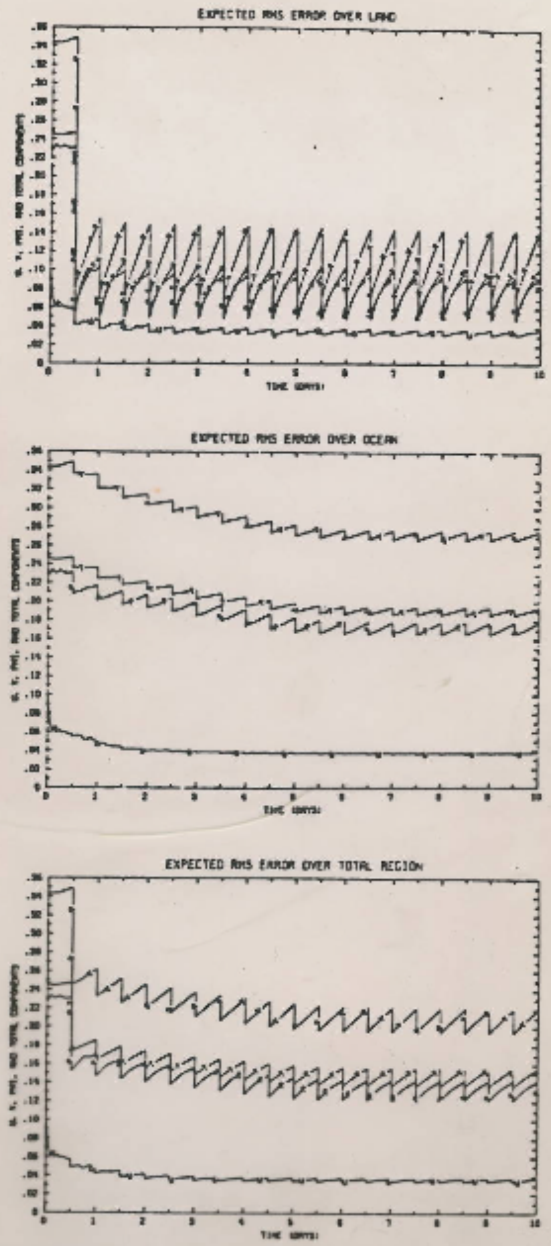


Fig. 6 This figure and the following ones show the properties of the estimated algorithm (2.11) in the presence of system noise, $Q \neq 0$. This figure gives the Erms estimation error, and is homologous to Fig. 2. Notice the sharper increase of error over land between synoptic times, and the convergence of each curve to a periodic, nonzero function.