An Observational Study of Tropical Large-Scale Fields Part II: A Modified Scheme of the Optimum Interpolation Method for Climatological Data Analysis in the Tropics

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(Manuscript received 31 August 1987, in revised form 1 August 1988)*

Abstract

A modified scheme of OIM – a zero-guess scheme – for direct estimation of the total value of meteorological fields at grid-points, independently from dynamical assimilation models, is developed and successfully tested over the sparse-network tropical region.

In its formulation, the ‘random empirical error’ (observational error + small scale noises) is shown to have a remarkable influence not only on other statistical parameters used in the scheme, but also on the weighting factors, the interpolation error, and therefore the grid-point values themselves.

Effective stations for each grid-point are selected using a search algorithm designed to fit the spatial structure of the statistical properties of the fields. A simple and steadily computable expression of the overall error at a grid-point is given, and the positive effects of low-pass filtering the data on this error is demonstrated.

The 5-year mean seasonal statistics obtained with these grid-point data show a significant consistency with both the observation and the existing statistics for which data from various sources were used in order to supplement the sparseness of the tropical observational network.

The generalization of this new scheme in order to use data from various sources, its applicability to climatological studies in the extratropics or its possible use in NWP assimilation schemes are to be investigated, keeping in mind that realistic estimates of statistical parameters should be used for the analysis.

1. Introduction

Recent meteorological data analyses have revealed the remarkable inter-annual variability of the atmospheric circulation within the tropics, and its significant teleconnection with the extratropics on global scale (Bjerknes, 1969; Philander, 1983; Meehl, 1987). Nowadays, tremendous efforts are being made for a more comprehensive understanding of the mechanism underlying these global phenomena through both data analysis and numerical modeling or simulations (Nihoul, 1985; Fein and Stephens, 1987).

As for the tropics, the basic state or climato-

logy is shown to carry most of the circulation variance (Krishnamurti, 1979). Smagorinsky (1983) notes that a better knowledge of the basic state fields is very important for acquiring a mechanistic understanding of the large-scale and long-term variations of the tropical circulation, and for improving our predictive skill for these variations. Particular attention should be paid to the annual march, because many of the inter-annual variations seem to be phase-locked to it (WCRP, 1985). However, two main difficult problems in obtaining this information arise here.

The first problem is the sparseness of the observational network in the tropics and, to-

gether with it, the shortness and/or the irregularity of the existing tropical data records. In spite of the intensive but costly global or regional weather experiments (FGGE, GATE, MONEX...) and the use of satellite data such as the Outgoing Longwave Radiation (OLR) and the cloud wind vector (Weickmann, 1985; Meehl, 1987), this sparseness is still far from being adequately supplemented. In fact, most of the available tropical statistics are obtained from local or regional studies, more or less centered over the relatively data-rich Pacific and Indian Basins (see Hastenrath, 1985; Chap. 6).

The second problem refers to the limitations of dynamical 4-dimensional data assimilation models to fit the tropical circulation (Puri and Gauntlett, 1987), especially in reconstructing the tropical divergence field (FGGE Data Catalogue, 1982; Heckley, 1985). This is shown by notable discrepancies among tropical grid-point statistics from different analysis centers (see GARP, 1985). These difficulties are due principally to the dependency of the analyses on the statistical and/or dynamical constraints allowed in the assimilation scheme in each of its vital steps: generation of the first-guess field, calculation of the statistical parameters, grid-point analysis, initialization and numerical forecast (GARP, 1978; Rosen *et al.*, 1985; Daley, 1985; Williamson and Daley, 1983).

The grid-point analysis – which is the transformation of the observational data at irregular stations onto a regular array of grids – plays a decisive role in these assimilation schemes, because it provides the initial values without which the Numerical Weather Prediction (NWP) cannot be finalized. Moreover, for climatological studies using observational data, the grid-point analysis is the key operation whose outputs give the diagnostic and large-scale image of the fields to be studied. In either case, the representativeness of these outputs is crucial for the success of the downstream operations to be performed with the so-obtained grid-point data.

Numerical processing of meteorological data necessarily involves a grid-point analysis step, which can be either subjective (=manual) (Newell *et al.*, 1972; Sadler *et al.*, 1987) or objective (=automated) (Lau and Oort, 1983; Hollings-

worth, 1987). Due to the need of high automation and the large amount of data to be handled, objective analysis methods seem preferable to the subjective ones. In general, objective analysis is performed as follows. First, a statistically (Gandin, 1963; Levitus, 1982; Oort, 1983) or dynamically (Rutherford, 1972) generated first-guess field (f_g^p) is assigned to the grid-point array. Then, station first-guesses (f_i^p) are interpolated using the nearest f_g^p (=forward interpolation). Finally, a linear combination of the differences between the observed data ($\hat{f}_i$) and the f_i^p at ' n ' selected stations around the grid g is used as a correction to f_g^p , in order to obtain the grid-point value f_g (=inverse interpolation or analysis) using

$$f_g = f_g^p + \sum_{i=1}^n w_i (\hat{f}_i - f_i^p) \quad (1)$$

where w_i are the weighting factors given by the specific analysis method.

Hollingsworth (1987) notes that objective analysis in general has paid most attention to the inverse interpolation, assuming the forward part to be a trivial operation. But Franke (1985) demonstrates that poor-quality forward interpolation schemes can seriously reduce the performance of even such powerful methods as the Optimum Interpolation Method (OIM). Moreover, the problems related to changes of coordinates and the balance of the first-guess field in multivariate assimilation schemes give even more importance to the accuracy in the forward interpolation. As for the tropics, the complexity of the basic dynamics makes it difficult to generate reasonable first-guess fields, and the non-validity of geostrophy does not allow multivariate analyses where geostrophy is used in deducing the wind-wind correlations from the height-height ones (Schlatter, 1975).

Recently, Julian (1984) discussed the need of developing an analysis scheme designed specially for climatological studies in the tropics. From the discussions above, it becomes clear that devising an objective analysis scheme free of dynamical model-dependency will contribute significantly to the fulfilment of this goal. This is the focal point of this work. For so doing, we take the OIM (Gandin, 1963) – which is the

most used analysis method (Carr, 1987) and the least dependent upon network density (Belousov *et al.*, 1968) – and choose (1) to perform grid-point analysis on univariate basis, with all the statistical parameters deduced and/or modeled from the observational data alone, and (2) to devise a scheme without first-guesses, in other words, a ‘zero-guess’ total field OIM (hereafter ‘the modified scheme of OIM’).

In these points, the present approach is fundamentally different from earlier works by Gandin (1963), Sumi (1981) or Julian (1984). Gandin (1963) attempts for a total field OIM by assuming $f_i^p = f_g^p$ in Eq. 1; but this approach was rejected later as inconvenient by Belousov *et al.* (1968). The other two authors search for an analysis method for the tropics by using the OLR data as a proxy to obtain the background rotational and/or divergent wind fields over data-sparse tropical areas. Sumi (1981) blends them with NMC forecasts as first-guesses for a modified Successive Correction Method (SCM), while Julian (1984) uses the divergent part together with the 12-hour ECMWF rotational wind persistences in a Schlatter-type OIM.

The main concern of this paper is to develop this modified scheme of OIM and to illustrate its applicability to tropical climatology. The outline of the scheme is given in Section 2, and its specific computational aspects are discussed in Section 3. As a corollary to it, a quantitative expression for the calculation of the grid-point analysis error (a measure of the accuracy of the analyses) is devised in Section 4. The positive effects of low-pass filtering of the original data on the analysis outputs is shown in Section 5. The applicability of this method for tropical climatology is illustrated in Section 6 where preliminary results on the annual march of the tropical circulation are given. Discussion and concluding remarks are given in the last section. Further analysis results on both the annual march and the interannual variability of the tropical circulation using the so-obtained grid-point statistics will be the object of a separate paper (Part III).

2. The modified scheme: a zero-guess OIM

Let $\hat{f}_i$ denote the observational data and f_i its large-scale value at the i -th station, then

$$\hat{f}_i = f_i + e_i \quad (2)$$

Here, e_i is defined as a random error which includes not only the observational error, but also the local irregularities due to small scale and high-frequency phenomena (=noise) at the i -th station. We call it the ‘Random Empirical Error’ (REE), instead of ‘observational error’ as in the literature.

For reasons to become clear later, we found it more convenient to formulate this modified scheme in terms of normalized values. So that the normalized value of f_g , the large-scale (total) field at the grid-point g , is given by a linear combination of normalized values of the observational (total) fields at the surrounding stations, as follows

$$f_g / \sqrt{C_{gg}} = \sum_{i=1}^n w_i \hat{f}_i / \sqrt{C_{ii}} + I_g / \sqrt{C_{gg}} \quad (3)$$

Normalization is made by dividing the total field values at points of interest by the root square of the corresponding large-scale ‘mean moments-products’ or ‘autocorrelations coefficients’ (C_{ii} , C_{gg}), defined by Papoulis (1965) as

$$C_{ii} = \overline{f_i^2}; \quad C_{gg} = \overline{f_g^2} \quad (4)$$

$I_g / \sqrt{C_{gg}}$ is the normalized interpolation error in evaluating the normalized large-scale grid-point value ($f_g / \sqrt{C_{gg}}$). The other symbols are as in Eq. 1.

At each grid-point, a measure of the mean-square interpolation error on a large number of realizations is given by

$$\overline{E_g^2} = \left(\frac{I_g}{\sqrt{C_{gg}}} \right)^2 = \left[\frac{f_g}{\sqrt{C_{gg}}} - \sum_{i=1}^n w_i \hat{f}_i / \sqrt{C_{ii}} \right]^2 \quad (5)$$

which yields

$$\begin{aligned} \overline{E_g^2} = 1 - 2 \sum_{i=1}^n \frac{w_i \overline{f_g (f_i + e_i)}}{\sqrt{C_{gg} \cdot C_{ii}}} \\ + \sum_{i=1}^n \sum_{j=1}^n \frac{w_i w_j \overline{(f_i + e_i)(f_j + e_j)}}{\sqrt{C_{ii} \cdot C_{jj}}} \end{aligned} \quad (6)$$

As in the literature, we assume the errors (REE) to be random, so that

$$\bar{e}_i = 0; \overline{e_i e_j} = e^2 \delta_{ij}; \overline{f_i e_i} = 0; \overline{f_i e_j} = 0 \quad (7)$$

where δ_{ij} is the Kronecker delta. Eq. 6 yields then

$$\begin{aligned} \bar{E}_g^2 = & 1 - 2 \sum_{i=1}^n R_{ig} w_i \\ & + \sum_{i=1}^n \sum_{j=1}^n R_{ij} w_i w_j + \sum_{i=1}^n M_{ii} w_i^2 \end{aligned} \quad (8)$$

where

$$R_{ik} = \overline{f_i f_k} / \sqrt{C_{ii} \cdot C_{kk}}; \quad k = i, j, g \quad (9)$$

and

$$M_{ii} = \bar{e}^2 / C_{ii} \quad (10)$$

are the normalized autocorrelations of the large-scale fields, and the measure of the REE, respectively. Discussions on the statistical parameters used in the present scheme of OIM are given in the next section. Under the condition of

minimum $\bar{E}_g^2$ (i.e., $\frac{\partial \bar{E}_g^2}{\partial w_i} = 0$), Eq. 8 gives the following system of n linear equations, from which the optimal weights (w_i) are deduced

$$\sum_{j=1}^n R_{ij} w_j + M_{ii} w_i = R_{ig}, \quad i = 1, 2, 3, \dots, n \quad (11)$$

Discussions in Gandin's monograph (1963) show that, in the case of total field OIM, the weighting factors should be normalized in order to obtain realistic analysis outputs. This is done

by requiring that $\sum_{i=1}^n w_i = 1$. The so-normalized w_i are used hereafter. The optimal $\bar{E}_g^2$ are then given by

$$\bar{E}_g^2 = 1 - \sum_{i=1}^n \sum_{j=1}^n R_{ij} w_i w_j - \sum_{i=1}^n M_{ii} w_i^2 \quad (12a)$$

or

$$\bar{E}_g^2 = 1 - \sum_{i=1}^n R_{ig} w_i \quad (12b)$$

These parameters are used in Eq. 3 to evaluate the normalized grid-point total large-scale value,

which is expected to be within

$$\sum_{i=1}^n w_i \hat{f}_i / C_{ii} \pm \sqrt{\bar{E}_g^2} \quad (13)$$

with a confidence limit of about 70% as shown in Hasebe (1980).

The normalized formulation is adopted here for the following reasons: 1/ the assumption of homogeneity is more fulfilled for the R_{ij} than for the local-dependent C_{ij} , making the numerical modelling of R_{ig} much easier; 2/ digital computations (numerical fitting, matrix solving, etc...) are more economical with the R_{ij} than with the C_{ij} , which are excessively large numbers; 3/ grid-point errors can then be directly estimated in terms of their relative values, giving the error-to-signal ratio for each of the components of the total analysis error (Section 5). Dimensional large-scale values can be obtained by multiplying the normalized analyses by the corresponding C_{gg} calculated as distance-weighted averages of the C_{ii} at n selected stations around the grid of interest.

3. The analysis procedure

Practically, this modified OIM scheme is performed in four main steps. First, quality control and low-pass filtering of the time-series of the observational tropical upper-air wind data are performed. Secondly, the REE, the autocorrelations and the normalized autocorrelations are calculated, and then modeled to fit a non-isotropic function (Thiebaux, 1986; Franke, 1986). These two steps were the main concern of Part I (Sanga, 1986), where a simpler model was used for computational economy. Third, a search algorithm is applied to each grid-point in order to select the effective neighboring stations (see subsection 3.3) whose statistical parameters are used in the calculation of the weighting factors (Eq. 11) and the interpolation errors (Eqs. 12). Finally, values for the large-scale total field for the wind components (u , v) are calculated within the margin of interpolation error (Eq. 13) on a daily basis, for each 20 degrees of longitude and 5 degrees of latitude over all the tropical belt, on the isobaric 850 and 200 mb planes. This spatial scale resolution is representative for tropical large-scale phenomena, as recommended in

GARP No. 20 (1978, Table 2.1). The REE includes all those processes unresolvable on these time- and space-scales (=noise).

3.1 Data

The reader is referred to Sanga (1986) for a more detailed report on the data quality control and supplementing of missing or erroneous data. We use here the same time-series of 5-year (1979-1983) records of daily upper-air data from tropical stations. The low-pass filtering is performed with a Lanczos filter (cut-off period = 20 days), on 200 and 850 mb levels.

3.2 Estimates of the REE

The structure function defined by Gandin (1963) as follows

$$\hat{B}_{ij} = (\hat{f}_i - \hat{f}_j)^2 \quad (14)$$

is used to calculate the REE, after Yamamoto *et al.* (1985). After some manipulations using Eqs. 2 and 7, and considering the non-isotropy of the fields, $\log \hat{B}_{ij}$ is made to fit a linear function of the zonal and meridional distances between stations, respectively. This yields

$$\log_{x,y} \hat{B}_{ij} = \log_{x,y} [(\overline{f_i - f_j})^2 + 2\bar{e}^2] = \begin{cases} a_1 x + a_{0x} \\ a_2 y + a_{0y} \end{cases}$$

Noticing that at zero distance, $f_i = f_j$, and adopting $\max(a_{0x}, a_{0y})$ as the estimate of $\log \hat{B}_{ij}$, the REE is then given by

$$REE = \sqrt{e^2} = \sqrt{0.5 \exp[\max(a_{0x}, a_{0y})]} \quad (15)$$

REE is the estimate of e_i ; it gives the error in daily data, averaged over the network of stations. Table 1 gives the estimates of the REE for u and v (200, 850 mb) obtained from upper-air tropical daily data (1979-1983) for pairs of stations with $x, y \leq 750$ km. Notice that the values of REE obtained from low-pass filtered data are $1/2 \sim 1/3$ of those from non-filtered data. The decisive influence of the REE on the OIM outputs will become clear hereafter.

3.3 The autocorrelation and the normalized autocorrelation

Requirements for an OIM without first-

Table 1. The Random Empirical Error (REE) for the non-filtered data and the filtered u and v data (adapted from Sanga, 1986).

	u (m/s)		v (m/s)	
	850 mb	200 mb	850 mb	200 mb
Non-filtered data	2.2	3.0	2.8	3.2
Filtered data	0.7	1.3	0.9	1.3

guesses make us use much parameters as the mean moment-products (C_{ij}) and the normalized mean moment-products (R_{ij}) instead of the covariances and the correlation coefficients. These parameters are defined in Gandin (1963). Their mathematical properties are discussed by Papoulis (1965), who calls the C_{ij} (Eqs. 4, 16 and 17) the 'autocorrelation coefficients', and the R_{ij} (Eqs. 4, 18 and 19) the 'normalized autocorrelation coefficients'.

The above-defined autocorrelation coefficients, calculated from the observational data, are given by

$$\hat{C}_{ij} = \overline{\hat{f}_i \hat{f}_j} \quad (16)$$

which gives, after transformations using Eqs. 2 and 7

$$\hat{C}_{ij} = \overline{f_i f_j} + \bar{e}^2 \delta_{ij}$$

$\overline{f_i f_j}$ represents the autocorrelation of the large-scale fields, which can now be deduced from the observational data by using

$$C_{ij} = \overline{f_i f_j} = \begin{cases} \hat{C}_{ij} & \text{for } i \neq j \\ \hat{C}_{ii} - \bar{e}^2 & \text{for } i = j \end{cases} \quad (17)$$

These expressions show that using $\hat{C}_{ii}$ in the OIM will overestimate the large-scale C_{ii} by $\bar{e}^2$, introducing some non-negligible distortions in the analysis outputs. In general, the use of first-guesses in the calculation of statistical parameters (in terms of 'observation-minus-forecast' or climatology errors) gives way to even larger overestimates of the 'true' variances by $\bar{e}_o^2 + \bar{G}^2$, where e_o is a measure of the 'instrumental error', and G the first-guess error (Schlatter, 1975).

If the normalized autocorrelation coefficients of the observational data are expressed as

$$\hat{R}_{ij} = \frac{\hat{C}_{ij}}{\sqrt{\hat{C}_{ii}\hat{C}_{jj}}} = \frac{\hat{f}_i\hat{f}_j}{\sqrt{\hat{f}_i^2\hat{f}_j^2}} \quad (18)$$

then, the corresponding expression for the large-scale fields is given by

$$R_{ij} = \frac{C_{ij}}{\sqrt{C_{ii}C_{jj}}} = \frac{\hat{C}_{ij}}{\sqrt{\hat{C}_{ii}\hat{C}_{jj}}} \times \frac{1}{\sqrt{(1-\alpha_i^2)(1-\alpha_j^2)}}$$

or

$$R_{ij} = \begin{cases} \hat{R}_{ij} \cdot \beta_{ij} & \text{for } i \neq j \\ 1 & \text{for } i = j \end{cases} \quad (19)$$

where

$$\beta_{ij} = \sqrt{(1-\alpha_i^2)(1-\alpha_j^2)} \quad (20)$$

and

$$\alpha_i^2 = \bar{e}^2 / \hat{C}_{ii} \quad (21)$$

(both expressed as a percentage; $0 < \alpha_i^2 < 1$) indicate the fitness of the observational $\hat{R}_{ij}$ to represent the large-scale R_{ij} , and the error-to-observational signal ratio, respectively.

Equation 19 shows that $\hat{R}_{ij}$ underestimates R_{ij} owing to the existence of observational error and small-scale noise. This R_{ij} is a limiting value to which $\hat{R}_{ij}$ tends if the REE (and therefore the α_i^2) decreases. Thus any method which can reduce the REE is expected to give better estimates of the large-scale R_{ij} and C_{ij} . Thus, Eqs. 17 and 19 confirm theoretically the empirical results in Sanga (1986), where it was shown that low-pass filtering of the observational data enhances the spatial correlations, while reducing REE.

Then a second order autoregressive non-isotropic function, $R(x,y)$, mathematically and statistically discussed by Thiebaux (1976, 1986) and Franke (1986), is modeled to fit the so-obtained R_{ij} .

$$R(x, y) = [\cos bx + (a/b)\sin bx] \exp(-ax)$$

$$X[\cos dy + (c/d)\sin dy] \exp(-cy)$$

(22)

where x and y are the zonal and meridional

Fig. 1. The searching area for effective stations. Thin lines indicate the non-isotropic normalized autocorrelation field modeled by Eq. 22. Thick lines enclose the corresponding areas for isotropic search with a cut-off radius equal to the zonal (X) or meridional (Y) scale lengths respectively. In either case, the isotropic search neglects highly correlated stations along the major axis and favors lowly or negatively (shaded) correlated stations along the minor axis.

distances respectively, and a , b , c and d the regression coefficients (Fig. 1).

This $R(x,y)$ shows characteristics similar to those obtained in Sanga (1986) with a simpler cosine-damped linear model: 1/ homogeneity, but clear non-isotropy for not only for the wind field, but also for the temperature and the geopotential fields as well; 2/ Dependency on altitude; 3/ larger spatial normalized autocorrelations for low-pass filtered data than for non-filtered data, ensuring larger interpolation ranges for OIM. Results comparable to points 1 and 2 for the extratropics are given for the correlation function by Thiebaux (1986) in a contemporary work to Sanga (1986).

3.4 The noise-to-signal ratio

The parameter M_{ii} , which is the normalized REE at each station (Eq. 10), gives the ratio of the noise to the 'true' large-scale field. It is essentially a noise-to-signal ratio. Its magnitude depends on both the estimate of this large-scale field and the accuracy of the observation, from which its calculation is straightforward:

$$M_{ii} = \bar{e}^2 / C_{ii} = \bar{e}^2 / (\hat{C}_{ii} - \bar{e}^2) \quad (23)$$

or

$$M_{ii} = \alpha_i^2 / (1 - \alpha_i^2) \quad (23)$$

Low-pass filtering is shown to reduce significantly the REE (Sanga, 1986), and, therefore, the magnitude of M_{ii} . This is more likely to yield better analysis results, in agreement with Seaman (1981) who notes that the analysis will fit the observation better in case of a small noise-to-signal ratio than in case of a larger one (noisy observations).

3.5 A non-isotropic search algorithm

The search for effective stations for each grid-point is performed by successive scanings ($m=1,2,3,\dots$) over elliptical zones, in order to conform with the spatial structure of the so-modelled $R(x,y)$ (Fig. 2). Successively, each grid-point is taken as the center of an ellipse, with the axes given by

$$a_x=0.1 mX$$

$$a_y=0.1 mY$$

where X and Y — the scale lengths — are distances at which $R(x,y) = 0.5$ along the x- or y-axis, respectively.

An earlier non-isotropic search made by selecting stations with largest correlation-to-longitude ratios is given by Davidsson and McAvaney (1981). In the present model, non-isotropic and elliptical scanings, based on the statistical properties of the large-scale fields, make it possible to perform analysis with distant but highly correlated stations along the major axis of $R(x,y)$, while neglecting closer but lowly or negatively correlated stations along the minor axis. This is a significant improvement — especially over data-sparse areas — as compared to isotropic scanings (Schlatter, 1975; Hasebe, 1980) which act mostly the opposite way (Fig. 1).

Interpolation is then performed using the data

Fig. 2. The large-scale patterns of the normalized analysis error (Eqs. 26-28; in percentages of $C_{\theta\theta}$): a) the interpolation error $q(H)$, b) the $Q(E_o)$, and c) the overall analysis error E for the non-filtered zonal wind at 200 mb. The corresponding values for the zonal and meridional means are also given.

from a maximum of 5 selected stations (Belousov *et al.*, 1968) which are far enough from each other and whose statistics yield positive $\sum_{i=1}^n w_i R_{i,q}$. This procedure avoids the 'screening effects' (Gandin, 1963) and keeps $\bar{E}_g^2 \leq 1$ (Eq. 12b).

4. Errors in objective analyses

Following Koehler (1979), Franke (1985) demonstrates the determinant impact of the forward interpolation on the performance of objective analysis methods. He shows that the grid-point overall error (E) can be decomposed into independent components, and discusses ways of reducing them. Although his formulation seems to work well with simulated first-guesses and observed data, its quantitative applicability to real data is not clearly demonstrated.

It is shown hereafter that these quantitative estimations are possible within the framework of the present modified scheme of OIM. Suffice to recall that interpolation in this scheme is made from stations to grid-points only (Eq. 3), with the normalized grid-point analysis data (F_g) given by

$$F_g = \sum_{i=1}^n w_i (f_i + e_i) / \sqrt{C_{ii}} + \sqrt{\bar{E}_g^2}$$

Replacing e_i by $\sqrt{e^2}$ without losing any generality, we obtain

$$F_g = \sum_{i=1}^n w_i f_i / \sqrt{C_{ii}} + \sum_{i=1}^n w_i \sqrt{M_{ii}} + \sqrt{\bar{E}_g^2} \quad (24)$$

Let H denote the normalized large-scale (true) value, E_o the normalized REE, and Q the linear operator used for interpolation, then Eq. 24 can symbolically be represented by

$$F_g = H + E = Q(H + E_o) = Q(H) + Q(E_o)$$

or

$$F_g = H + q(H) + Q(E_o) \quad (25)$$

$Q(E_o)$ is the error due to the REE in interpolating from stations to grid-point, while $Q(H) = H + q(H)$, which $q(H)$ the interpolation error in approximating H by its interpolated value $Q(H)$.

A simpler and more easily computable expression of the analysis error can then be obtained from Eqs. 24 and 25 by

$$E = Q(E_o) + q(H) \quad (26)$$

where

$$q(H) = \sqrt{\bar{E}_g^2} \quad (27)$$

and

$$Q(E_o) = \sum_{i=1}^n w_i \sqrt{M_{ii}} \quad (28)$$

E is a measure of the accuracy of the analysis expressed in terms of error-to-signal ratio, and consists of two components: the interpolation error-to-signal ratio ($q(H)$), and the noise-to-signal ratio ($Q(E_o)$). The dependency of $Q(E_o)$ upon the REE is obvious. The relationship between $q(H)$ and the REE will be discussed in the next section.

5. Dependency of the interpolation error on the REE

The dependency of the interpolation error on the correlation coefficients was discussed in Belousov *et al.* (1968) — and this can be seen easily here in a similar expression (Eq. 12b) for the normalized autocorrelations. Gandin (1963) discusses the relationship between the 'observational error' and the interpolation error, under the condition of positive weights w_i .

We revisit this problem for $\bar{E}_g^2$ and REE, for any w_i . Considering the symmetry of the normalized autocorrelation matrix, the derivatives of Eqs. 11 and 12b give after some manipulations

$$\frac{\partial \bar{E}_g^2}{\partial M_{ii}} = \sum_{k=1}^n w_k^2 \quad (29)$$

This relation demonstrates that $\bar{E}_g^2$ and M_{ii} (and therefore REE) are directly proportional, so that smaller REE are more likely to yield smaller interpolation errors.

This result and those obtained in the Section 4 show that all the entries in the OIM — and therefore the grid-point values themselves — are deeply dependent on the estimate of the REE. Thus, procedures — such as low-pass filtering — which reduce the REE will impact positively on

the grid-point estimates. It is then expected that analysis with filtered data will give better estimates of grid-point values than those with the raw data.

6. Preliminary analysis results

Several methods are available for appraising the analysis quality (Daley and Meyer, 1986). Seaman and Hutchinson (1985) note that the obvious requirement is that the analyses fit the observations, within the margin of analysis errors and for the time and space scales being represented. However, this true picture of observational patterns is yet to be established. Therefore we turn to some 'classical' long-term tropical statistics (such as Newell *et al.*, 1972; Oort, 1983; Krishnamurti *et al.*, 1983...) to assess the validity of our method and its applicability to the tropical climatology. First of all, grid-point analysis errors will be given in order to ascertain the reliability and the accuracy of our 5-year statistics. Then, results on the annual march of

the tropical circulation are presented and discussed. Further analyses and discussions on the intra- and inter-annual variations will be given in a separate paper (Part III).

6.1 The grid-point analysis error

Estimates of the analysis errors for u are given in Figs. 2 and 3 in terms of percentages of $\sqrt{C_{qq}}$. These figures depict the large-scale patterns of $q(H)$, $Q(E_o)$ and E (Eqs. 26-28), together with their zonal and meridional ($20^\circ\text{N} - 20^\circ\text{S}$) mean values, for the non-filtered and the low-pass filtered wind data.

Consistent with the REE for station data (Sanga, 1986), $Q(E_o)$ shows smaller values for the low-pass filtered data (max. 5%) and larger ones for the non-filtered data (max. 20%). The local dependency of this error is manifested in the longitude-latitude cross-section by larger values in the equatorial areas where the winds are normally weak and noisy. The same features are observed in the zonal and meridional means of $L(E_o)$ as well.

Fig. 3. Same as in Fig. 2, but for the low-pass filtered data.

Similarly, estimates of $q(H)$ are sensibly reduced by low-pass filtering, as expected (Section 5). The large-scale patterns show larger values over the data-sparse regions in the Eastern Pacific, the Indian and the Atlantic Oceans. This signature of dependency on filtering and observational network density is seen in both the zonal and the meridional mean values, as well: 1/ larger values in data-void areas, with a remarkable maximum in the Eastern Pacific; 2/ sensibly smaller errors for the filtered than for the raw data. Therefore, only results for filtered data will be discussed hereafter.

Estimates of $q(H)$ are far larger than those of $Q(E_0)$, so that $E \sim q(H)$. The magnitudes of these errors for the seasonal statistics are about 0.5~1 m/s for the grid-point values and 0.3 m/s or less in the zonal and meridional means (Fig. 5, 7). This agrees with Oort (1983) who states that reasonable values for the error in the monthly zonal mean u would be about 1 m/s or lesser for longer averaging periods (season, year,...), on which a supplementary reduction due to the smoothing effect of the analysis procedure should be applied. Similar comments can be found in Hollingsworth and Lonnberg (1986).

6.2 The long-term annual march of the zonal wind

a. Large-scale zonal wind patterns

The large-scale patterns of 5-year zonal wind seasonal statistics ($\bar{u}$) (Figs. 4a, b) depicts the tropics as a zone of dominant lower easterlies (upper westerlies) in which bands of westerlies (easterlies) appear, grow and decay, following the solar annual march, in strong relationship with the summer monsoons in both hemispheres. The strongest activity is observed during the Indian monsoons when the upper easterlies cover all the Eastern Hemisphere from 10°S northward. In winter, strong lower easterlies (trade winds, $\bar{u} > 5$ m/s) and upper westerlies (anti-trade winds, $\bar{u} > 15$ m/s) blow steadily over the regions poleward of 5~10 degrees in both hemispheres. This seasonality of the tropical wind is not observed over most of the Western Hemisphere and poleward of 10°S in the Southern Hemisphere, where both the trades and the anti-trades are permanent all year long. The amplitude of these steady winds is modulated by the solar march, with maximum values during June-August (JJA). Similar features can be seen in Newell *et al.* (1972) and Webster (1987, Fig. 1.1).

Fig. 4a. Long-term (5-year) seasonal mean zonal wind field (contours at 2.5 m/s intervals) for low-pass filtered data for DJF and JJA, at 850 mb. Shaded areas denote westerly zones. Coordinates are given in degrees.

Fig. 4b. Same as Fig. 4a, but for 200 mb, with shaded areas denoting easterly zones and contours drawn at 5 m/s intervals.

This asymmetric behaviour between the Northern and Southern, or the Eastern and Western Hemispheres is manifest in the 200 mb large-scale circulation patterns (Fig. 4b). Here, bands of easterlies appear along the equator, with centers of activity over South America and Africa-Maritime Continent. During the northern summer (June to September), strong easterlies ($\bar{u}_{\max} > 20$ m/s) cover all the Eastern Hemisphere from 10°S northward. The southern maximum (DJF) is weaker (5 m/s), smaller in coverage and shorter in time (January-February). These peak periods are clearly separated by two transition periods (not shown) during which the easterly band crosses the equator, on its seasonal move from South to North (April) or vice versa in November.

A small and weak ($\bar{u} \sim 5$ m/s) easterly band with a peak period during the southern summer, is located over South America. Upper westerlies cover this region totally in JJA, when the easterly band is moved northwestward, off the West coast of Central America (Krishnamurti *et al.*, 1983). A nearly permanent zone of strong westerlies is observed in the Central Pacific (140°W , 15°N), out of phase with the Northern Hemisphere easterly band: minimum in JJA, maximum in DJF. In general, lower westerlies

(easterlies) tend to underly upper easterlies (westerlies).

b. Zonal and meridional means of u

Zonal mean $\bar{u}$ (Fig. 5) shows easterly winds over all latitudes on 850 mb. A symmetric structure, with a node on the equator, is found in spring and fall (not shown). Maximum winds (3–5 m/s) occur in the winter hemisphere, while weak ones (~ 2 m/s) are found in the summer hemisphere, separated by a node of very weak winds (0–1 m/s) at nearly 5°N (JJA) or 5°S (DJF). Riehl (1979; Fig. 1.2) gives similar results over the tropical oceans. It is important to note that zonal averaging eliminates the summertime westerlies in these maps, mostly because these westerlies occur simultaneously with the strengthening of easterlies (Newell *et al.*, 1972).

The 200 mb zonal mean $\bar{u}$ is westerly in DJF, with small speeds near the equator and very large ones (up to 15 m/s) poleward of 10 degrees in both hemispheres. Notable weakening of these westerlies, and their eventual reversal, occurs in JJA from 5°S northward. South of this latitude, the westerlies remain strong all year long, although DJF winds seem weaker (~ 7.5 m/s) than JJA ones (~ 15 m/s).

Meridional means of $\bar{u}$ over the 20°N to 20°S

Fig. 5. Long-term (5-year) seasonal statistics for the zonal mean (upper figures) and the meridional mean (lower figures) of the zonal wind, drawn within the margin of interpolation error.

belt (Fig. 5) show a considerable longitudinal structure modulated by the seasonal changes, as discussed by Webster (1983). In general, seasonal wind reversal seems to be restricted to the Eastern Hemisphere, especially over the Indian monsoons region, on both levels. The Western Hemisphere is dominated by weak lower easterlies (max. ~ 3 m/s) underlying relatively strong upper westerlies (maximum in DJF over the tropical open seas). There is nearly no seasonal change in the intensity of the easterlies over Central and Eastern Pacific at 850 mb. Due to this longitudinal structure, Newell *et al.* (1972) state that zonal averages are not expected to characterize the flow at any particular tropical latitude, excepted in a very general sense.

6.3 Long-term annual march of the meridional wind

The meridional wind (v) is very difficult to measure directly. However, the role of meridional transport of heat, momentum, mass and water vapor in the tropics is so important,

and the mutual interplay between the meridional and the zonal circulations on seasonal and interannual time-scales is so crucial, that any effort to assess the tropical v has significant merit by itself.

a. Large-scale meridional wind patterns

The 850 mb meridional wind 5-year mean seasonal statistics are predominantly northerly during DJF and southerly in JJA with dominant winds blowing from the winter hemisphere (Fig. 6a), the opposite being true at 200 mb (Fig. 6b). Some important features are to be noticed at 850 mb: 1/ the nearly 3-wave pattern of southerlies over the southern and eastern Africa, Brazil and Australasia, which widen and extend northward in JJA; 2/ the band of northlies stretching from the Atlantic to the Northern Pacific, through the Arabian Sea and Southeast Asia during JJA. This circulation gives way to remarkable convergence in the equatorial region, with a peak over the monsoons area. Newell *et al.* (1972) link a similar finding to the intertropical Convergence Zone

Fig. 6a. Same as Fig. 4a, but for the meridional wind (850 mb), with contours drawn at 0.5 m/s intervals. Shades denote southerly zones.

Fig. 6b. Same as Fig. 4b, but for the meridional wind (200 mb), with contours drawn at 2 m/s intervals. Shades denote northerly zones.

(ITCZ). 3/ the nearly permanent northerly wind over North Africa all year long, with a maximum during the northern ‘dry season’ (DJF). Dominant winds blow from the Summer Hemisphere at 200 mb. In DJF, strong southerlies ($\bar{v} > 4$ m/s) with a 3-wave pattern over the Northern Hemisphere, replace the weak summer-

time northerlies ($\bar{v} \sim 2$ m/s). The biggest wind reversal is observed over North Africa and Indochina, where these southerlies are maximum. These winds are permanent over South Pacific and East Africa.

b. Zonal and meridional means of $\bar{v}$

The above-mentioned features are well marked in the zonal mean of $\bar{v}$, which shows that the cross-equatorial flow is mostly from the Winter Hemisphere at 850 mb and from the Summer Hemisphere at 200 mb (Fig. 7). The JJA zonal mean circulation depicts a typical Hadley Cell: lower equatorward flow converging at nearly 10°N , with upper poleward flow. This pattern is consistent with the move of the ITCZ during this season, especially over the region from East Africa to the data-line (Triplet and Roche, 1977, Fig. 9.14). The DJF zonal mean circulation is more complex.

The existence of the remarkable longitudinal structure in the meridional mean of $\bar{v}$ (Fig. 7) indicates that the zonal mean Hadley Circulation has only a very broad sense, while 'local Hadley Cells' at different longitudes, and their complex interplay with the longitudinally varying zonal circulation, are the key elements for understanding the mechanism of interannual variabilities of the tropical large-scale circulation and such phenomena as the ENSO.

This meridional mean $\bar{v}$ can be seen as a index of the cross-equatorial flow averaged over each longitudinal band. It appears from Fig. 7 that local Hadley Cells with stronger low/upper level cross-equatorial flow from the winter/summer hemisphere tend to be located over the three tropical convective zones. The opposite occurs over East Pacific, the Atlantic and Indian Oceans. A nearly perfect seasonal wind reversal is observed at 200 mb, with the biggest change at around 100°E : 2 m/s in DJF and -2 m/s in JJA.

6.4 The wind velocity statistics

The results obtained above can be put together and discussed in terms of wind velocity fields (using 5-year monthly mean statistics) in order to have a global picture of the tropical circulation (Figs. 8, 9). At 850 mb in July (Fig. 9) strong trade winds prevail over the Southern Hemisphere, the Amazonia and the northern West Pacific, just on the equatorward flank of the Mascarene, the Australian, the North and South Atlantic, and the North Pacific Highs (see Hastenrath, 1985; Fig. 6.1.2 and Table 6.3.1).

Fig. 7. Same as Fig. 5, but for the meridional wind.

Fig. 8. 5-year monthly mean of wind velocity for January at 850 and 200 mb. North is on the top of the charts, and East on the right. Wind direction is given by the arrows, with lengths proportional to the wind speed indicated by isotachs (m/s).

Fig. 9. Same as Fig. 8, but for July.

The low-level Findlater (Somali) Jet is shown then by maximum southeasterlies North of Madagascar which give place to strong south-westerlies over the Arabian Sea, after crossing the equator off East Africa (Findlater, 1977).

At 200 mb, the Subtropical Westerly Jet (SWJ), embedded in the strong antitrades poleward of 10 degrees, dominates the wintertime circulation of both hemispheres (Figs. 8,9). This jet persists all year long over the Northeast Pacific, in agreement with Krishnamurti *et al.* (1985). Its 3-wave pattern in DJF presents peaks over East Atlantic, the Arabian Sea and the Northeast

Pacific, downstream and equatorward of the midlatitudes ridges observed by Krishnamurti (1979) and Arkin *et al.* (1986). During the northern summer, this SWJ is swiftly replaced by the Tropical Easterly Jet (TEJ), covering the region from Southeast Asia to the Atlantic with strong upper-level easterlies (> 15 m/s), in relationship with the strengthening of the Tibetan High. This wind system is shown to be deeply involved with the summer monsoon rainfall over West Africa and Asia (Flohn, 1964). Further investigations of its behaviour and its possible role in the process of interannual vari-

ability of the tropical circulation are needed.

The upper-level zonal mean wind velocity (Fig. 10) shows a clockwise change in direction North of 5°S , with southwesterlies from November to April and northeasterlies from July to October (Fig. 10). The burst of the monsoons (TEJ) when strong westerlies (SWJ) are quickly replaced by easterlies in June (and vice versa in October) is also reported by Palmén and Newton (1969). South of 10°S , there is no reversal of wind velocity, but a remarkable weakening in DJF. At the 850 mb level, strong trade winds dominate the tropical 'dry season' circulation (April-October in the Southern Hemisphere and October-April in the Northern Hemisphere). These winds are weak (less than 2 m/s) along the equator (the doldrums) and over the Summer Hemisphere.

Altogether, these features show observational and dynamical consistency with the other fields (pressure, temperature, cloudiness, the annual march of the Hadley Cell, ITCZ...) as summarized in Newell *et al.* (1972) and recently in Hastenrath (1985, Chap. 6).

7. Discussion and concluding remarks

The analysis results obtained in this work present very consistently the main features of the tropical large-scale circulation, in good agreement with both the observation (Hastenrath, 1985)

and the existing statistics, within the margin of the analysis errors. Most of the other statistics are obtained by blending data from various sources (stations, satellites, ships...) in subjective methods (Newell *et al.*, 1972) or more sophisticated objective analyses (Oort, 1983; Krishnamurti *et al.*, 1983; Arkin *et al.*, 1986).

In general, our wind field statistics are closer to Newell's than those from Oort, which tend to be larger over regions of wind maxima. These authors use averages of available data within a latitude belt as zonal means (and as first guesses for Oort), implying more representativeness for data-rich regions and some bias in data-void areas, whose station data might have been eventually rejected as erroneous.

Analyses by Arkin *et al.* (1986) are obtained from the NMC operational NWP and cover nearly the same period of time as ours (October 1978-November 1983). Considering the level of sophistication and complexity of this data assimilation system (Dey and Morone, 1985) – and therefore its computational costs – the good agreement with our statistics (200 mb) shows the ability of our simple method to produce comparable statistics from a reduced set of dispersed upper-air data.

However, the main point of disagreement with these three sets of statistics is about the 200 mb circulation in JJA over the equatorial Central and

Fig. 10. The annual march of the 5-year monthly mean zonal mean wind velocity over the tropics, on 850 and 200 mb levels. North is on the top of the charts, and East on the right. Wind direction is given by the arrows (North is on the top and East on the right of the panel) with lengths proportional to the wind speed indicated by isotachs (m/s). Winds stronger than 2 m/s (850 mb) or 5 m/s (200 mb) are shaded.

East Pacific and the Americas. Our results over these regions (= Western Hemisphere) show prevailing westerlies (~ 5 m/s) in which a small band of easterlies migrates from the Amazonia (DJF) to the West coast of Central America (JJA), in relationship with the tropical rainy season. In the other analyses, a band of weak easterlies stretches all over this region (JJA), contrarily to our general knowledge about the Walker Circulation (Bjerknes, 1969): lower easterlies and upper westerlies over the Central and East Pacific.

Krishnamurti *et al.* (1983) use spherical harmonics to fit the monthly mean data. Their results depict nicely these observational features of the annual march of the tropical circulation. (Charts A1-12). Their July 200 mb circulation (Chart A7) is dominated by a huge zone of upper easterlies from Asia to mid-Atlantic, and a smaller one off Central America. They relate these wind systems to the strong Tibetan High and to a relatively weaker one over Central America, respectively. These results compare very consistently with both the observations and Figure 4b.

In general, lower (upper) westerlies (easterlies) are shown to be deeply involved with the summer monsoons (rainy). As a large-scale picture of the rains associated to these monsoons is difficult to obtain, we think that there are some promising prospects in finding out if these dominant winds (especially the TEJ) could be used for monitoring the strength and the variability of the tropical monsoon rainfalls. Moreover, the asymmetry of these winds between the Northern and Southern Hemispheres, or between the Eastern and Western Hemispheres shows the difficulty in generalizing from the Indian monsoon system, which has received most of the attention up to now (Webster, 1987; Fig. 1.10). This complexity of the tropical circulation is manifested in the longitudinally varying structure of both the Walker and the Hadley Circulations, implying that interactions between these two systems on regional scale are crucial for the interannual variability of the global tropical circulation.

The consistency of the statistics obtained with the present method is encouraging us to use them

for further analyses. This performance is due to the fact that we took account of the true properties of the tropical fields in each step of our model (modelling the statistical parameters, search algorithm, estimation of cut-off period for low-pass filtering...), independently from any dynamical constraint. On a practical level, the non-dependency on dynamical assimilation schemes implies simplicity – and economy – in the computations. This is a desirable result especially for those climatologists who possess long data records but no access to any data assimilation center.

Furthermore, a quantitative estimation of the analysis error is made available, contrary to the other methods (Rosen and Salstein, 1987). Lorenc (1986) notes that there is no specific meaning in comparing the magnitude of the errors by different analysis methods. However, their estimation remains fundamental because they give the accuracy of the analysis outputs – and the same is true for any physical quantity.

At present, the main limitation in this method is its ability to analyze data of only one type at once (here, upper-air data). Further investigation should be done to achieve generalization and more versatility, in order to accommodate simultaneously data from various sources. Problems related to the evaluation of the $C_{\theta\theta}$ are still the real bottleneck in the various OIM schemes, and require more attention in the future. Finally, we suggest that it would be interesting to test the applicability of this scheme to extratropical climatology, or its possible use in NWP assimilation schemes.

Acknowledgment

We express here our deep gratitude to Prof. R. Yamamoto for his patience and encouragements in supervising this work. We acknowledge Prof. T. Iwashima, Dr. T. Yasunari and the many anonymous reviewers for their criticism, comments and relevant suggestions.

The computations were performed on the FACOM M340R Computer System of the Laboratory for Climatic Change Research, Kyoto University.

Appendix

(Table A1).

The historical review of analysis methods

Table A1. Historical review of analysis methods used for climatology (CLM) or NWP. These methods are subjective (A) or objective using either station statistics (B) or NWP outputs (C). Domain of application: global (G), Northern Hemisphere (N), Southern Hemisphere (S), the tropics (T) or non-specified (?).

Authors (date)	Scheme	Remarks
up to 1949	nearly A only	synoptic, climatological maps
Panofsky (1949)	C(NWP, N)	3-order polynomial large-scale fitting: need of matching and smoothing
Gilchrist and Cressman (1954)	C(NWP, N)	2-dim. fitting of 2-order polynome, using data around the grid-point: geostrophic assumption, numerical first- guesses; constant search area
Eliassen (1954)	C(NWP, N)	Optimum interpolation for pressure anomalies. No specifications on the first-guesses.
Bergthorsson and Döös (1959)	C(NWP, N)	Successive Corrections with constant search area and forecasts as first-guesses.
Sasaki (1958, 1970)	C(NWP, N)	Objective analysis using Variational Methods
Creessman (1959)	C(NWP, N)	Successive Correction Method (SCM): successive scans of decreasing radius to correct the NWP first-guess field.
Gandin (1963)	B	Optimum Interpolation Method (OIM) using climaological first-guesses, isotropic and homogeneous statistical fields. Proposes the use of OIM in NWP schemes.
Bedient <i>et al.</i> (1967)	C(NWP, T)	Apply the SCM to tropical wind analysis. using wind data.
Newell <i>et al.</i> (1979)	A(T)	Subjectively drawn maps for tropical statistics (classic monograph).
Rutherford (1972)	C(NWP, N)	Adapts the OIM in NWP using forecast firstguess fields (4-dim.)
Sadler (1975)	A(T)	Subjective analysis of tropical upper- tropospheric circulation.
Schlatter <i>et al.</i> (1976)	C(NWP, G)	Global multivariate OIM using height anomalies and geostrophic assumption to obtain wind anomalies. NWP first-guesses
Bergman (1979)	C(NWP, G)	Same as above, but using temperature anomalies.
Lorenc (1981, 1986)	C(NWP, G)	Operational OIM in its current form
Davidson and McAvaney (1981)	C(NWP, T)	Adapt Schlatter's OIM for operational uses in the tropics (univariate+ variational adjustment).
Lau and Oort (1981)	A, C	Compare the GFDL subjective analysis and the NMC objective analysis statistics.
Sumi (1981)	C(CLM, T)	Modified SCM+OLR data for the tropics.
Levitus (1982)	B(G)	Global marine statistics using SCM
Oort (1983)	B(G)	Global monthly statistics using CRAM.
Krishnamurti <i>et al.</i> (1983)	B(T)	Tropical monthly statistics using Spherical Harmonics
Julian (1984)	B(T)	OIM (Schlatter)+OLR data (tropics).
LeDimet and Talagrand (1986)	C(NWP, ?)	Shows the relationship between the OIM, SCM and the Variational Method.
Bratseth (1986)	C(NWP, ?)	Shows the relationship SCM-OIM.
Carr (1987)	C(NWP, G)	Critical review of NWP objective analyses, especially the OIM.
Hollingsworth (1987)	C(NWP, G)	Critical review of NWP objective analyses, especially at the ECMWF.
Puri and Gauntlet (1987)	C(NWP, T)	Critical review of NWP in the tropics
Sadler <i>et al.</i> (1987)	A(T)	Subjective analysis of tropical marine data

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熱帯大規模場の観測的研究

第2部：熱帯における気候資料解析のための最適内挿法改良スキーム

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格子点の気象要素の値を、力学的同化を用いずに、直接算定する、改良 OIM スキーム（ゼロ直接スキーム）を開発し、テストした結果データ網の粗な熱帯域でもうまく適用できることがわかった。

その公式化において、ランダムな経験誤差（観測誤差＋小スケールノイズ）は、スキーム内で用いられる他の統計的パラメータのみならず、重み関数、内挿誤差、したがって格子点値そのものにも著しい影響を与えることがわかった。

各格子点値内挿のために有効な観測点は、場の統計的な特性の空間構造に合うようにつくられたアルゴリズムによって選択した。格子点での全誤差の、簡単に計算可能な式が与えられ、この誤差に対する低周波フィルターの有効性も示した。

これらの格子点値を用いた5年平均の季節平均値は、観測値および、熱帯の観測網のあらさを補完するためにさまざまなソースの資料を用いた既存の統計値と、非常に良い一致を見た。

さまざまなソースからの資料を用いるためのこの新しいスキームの一般化や、中高緯度の気候学的研究への応用、さらに数値予報の同化スキームにおける使用の可能性についても、解析のためのよりもっともらしい統計パラメータの算定をすることを念頭におきつつ、調べる。