Modifications to an Operational Numerical Weather Analysis System and Application to Rainfall

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(Manuscript received 6 July 1967, in revised form 19 October 1967)

ABSTRACT

Modifications are made to an operational numerical weather analysis procedure concerning, chiefly, generation of the first approximation and consistency of analyzed scale with information density, with a view to extending the scope of the procedure. The method developed is applied to the analysis of climatic normal and monthly total rainfall patterns with favorable results. It is considered that the method, properly adapted, is suitable for more general application to other scalar fields such as dew point, wind component, shorter period rainfall and even survey contour analysis.

1. Introduction

Cressman (1959) has described an operational numerical weather analysis scheme directed toward the analysis of constant pressure surfaces in the atmosphere. The method, briefly reviewed in Section 2, is a versatile one, and in applying it to other meteorological elements and scalar fields, it is often convenient to have some means of automatically generating, from the observed data itself, a suitable first approximation to the analysis. This is useful if analyses are not made regularly in time and continuity has not been established, or if there are no time variations of the scalar field at all. In applying the method to a sparse network of observations, it also appears desirable to modify the process of successively analyzing smaller scales of variation, to a procedure whereby adjustments to smaller scales are made only if the density of information is sufficient. The two aspects above have received some consideration in Sections 4 and 5 of this paper, and the suggested modifications have been implemented in a practical application (see Section 8 and later) to rainfall analysis. This application was selected because the characteristic highly variable nature of rainfall was expected to be very exacting on the analysis method.

Gandin (1963) has developed a statistical analysis procedure to minimize errors, in the least squares sense, at analysis grid points situated between observed data locations. The method is based on the direct use of the distance autocorrelation function and the fields of mean and standard deviation of the element being analyzed. It is rationalized in Section 3 that the Cressman influence function is intended to be representative of the characteristic distance autocorrelation functions for the scales of variation being successively analyzed. Accordingly, provision has been made in the implementation of the method developed to use the distance autocorrelation or regression functions if available, although no such functions were actually used in this study.

The requirement for explicit numerical filtering of successive analysis approximations is discussed and a filter is constructed (see Section 6), which is almost free of orientational defects. Experience with the Cressman method of analysis on elements other than those used here with different grids indicates that some form of explicit numerical filtering is required for best results. In general use of the Cressman method it is also desirable to employ a higher than linear degree of interpolation, and a suitable formula is selected, briefly discussed in Section 7, and used in the final applications.

2. The analysis model

The analysis method devised by Cressman (1959) starts with a first approximation available over a regular grid and converges to a final analysis in a series of iterations during which successive approximations to the analysis are gradually adjusted to fit the irregularly spaced observation values. During an iteration a correction C_i, computed from the difference between the observation and its interpolated value (see Section 7) in the approximate analysis, is extrapolated to a nearby grid point using a distance weighting function appropriate to that iteration. This distance weighting function has the form $W=(R^2-l^2)/(R^2+l^2)$, for $l<R$ and $W=0$ for $l\geqslant R$, where l is the distance between the observation point and the grid point, and R, measured from an observation point, is a characteristic distance beyond which corrections based on that observation are not applied. The distance R defines an effective lower limit to the analyzable scale for each iteration, and since the radius R is made to decrease with each iteration, larger scales of variation in the approximate analysis are

adjusted or corrected during the first iteration and successively smaller scales are adjusted during later iterations.

When all corrections from all data within a distance R of each grid point have been computed for an iteration, they are combined by a suitable averaging procedure. If C_i and W_i are, respectively, the series of corrections and distance weights from the N observations within a radius R of a grid point, the new approximation ${}^{P}B_G$ at a grid point is given by

$$ {}^{P}B_G = {}^{P-1}B_G + \sum_{i=1}^{N} C_i W_i / \sum_{i=1}^{N} W_i, \qquad (2.1) $$

where ${}^{P-1}B_G$ is the old value at the grid point and ${}^{P}B_G$ is the new value at the grid point after iteration number P. The values of ${}^{P}B_G$ may be smoothed after each iteration, using a numerical filter in order to achieve most acceptable results. In the correction equation (2.1), if there is only one piece of data in the sum, then at grid points removed from observation locations, no compromise with surrounding observations takes place. It is therefore advisable in practice to set R sufficiently large for all iterations so that suitable adjustment may occur. This requires reference to the amount of observed information available for the analysis over a range of scales of variation and leads to the modification outlined in Section 5.

3. Distance weighted corrections

On the basis of regression coefficients between observations of the same element at varying separations, Bergthorssen and Doos (1955) experimentally determined the form of the distance weighting function which was assumed to be isotropic and homogeneous. An expression of the form $b_l = A/(l^k + B)$ was derived for the regression coefficient b_l in terms of the distance l and constants A, B and k. Gandin (1963) has used the distance autocorrelation of the element being analyzed and the average and rms deviation fields directly, to determine the grid point values of the element from the observed values. The Cressman method, on the other hand, makes use of the regression concept for separate scales of variation and employs a series of iterations to gradually correct these in the analysis. While this procedure is desirable because it allows the data to be subjected to validity checks of gradually increasing severity, it appears that a statistical determination of the distance regression or correlation function appropriate to the field for the scale of variation being analyzed is preferable to the expeditious use of the distance weighting function $(R^2 - l^2)/(R^2 + l^2)$. In addition, the assumption of isotropy of the correlation function as used by Gandin should be examined, especially in cases of strong gradient of the element being analyzed. For example, it is very unlikely that an assumption of this isotropy is applicable in an analysis of wind speed at jet-stream level. This also applies to the analysis of broad frontal zones represented by thermal wind jets and therefore relates to temperature analysis in the atmosphere. It would be possible to obtain information on the correlation function for various scales of variation by numerically filtering a long series of manual analyses to obtain residual analyses not containing scales of wavelength greater than $2R$, for all values of R used in the iterations of the Cressman type analysis. If sufficient data were available, a further stratification on, say wind direction, would also be possible. Such a study would clearly be a large one, and would also require computation of mean and standard deviations in order to obtain appropriate corrections at a distance l from an observation point. This extensive study has not been undertaken here, although the use of an assumed functional form for the non-isotropic influence function and information-density modified values of R have been applied in practice for meteorological differential analysis in the Australian region (Maine and Seaman, 1967). In this application to rainfall only empirical information-density modifications to R have been used and it is likely, except in the case of broad-scale rainfall patterns, that an orographic effect will be a greatly complicating factor on the total correlation function.

4. A statistically based first approximation

Where there is no useable time relationship based on previous analyses, a suitable value for the first approximation field can often be obtained by using the mean value of all the observed data in the analysis as a starting value at each grid point. A somewhat better approximation, if sufficient data are available, would be to group the data according to sub-areas of the grid and use the means of these groups as starting values within sub-areas. An improved approach and one which was attempted in the application to rainfall analysis is as follows.

If B_0 represents an observed datum a distance l from a grid point where an estimated B_G is required on a least-square-error basis, then

$$ B_G - \bar{B}_G = b_l (B_0 - \bar{B}_0), \qquad (4.1) $$

where $\bar{B}_G$ and $\bar{B}_0$ are averages with respect to time at the grid point and the observation point, respectively, and b_l is the regression coefficient for B_G on B_0. Introducing now the standard deviations S_G and S_0 at grid point and observation point, respectively, and the distance autocorrelation r_l for the distance l we have from (4.1),

$$ B_G = r_l (B_0 - \bar{B}_0)(S_G/S_0) + \bar{B}_G. \qquad (4.2) $$

Thus, a least-squares estimate may be obtained if the distance autocorrelation function is known for each point and the two-dimensional fields of mean value and standard deviation are known. It may be expected that these parameters in the case of meteorological data will be time dependent in themselves, and that the r_l may be a non-isotropic function of the scale of variation being analyzed. However, within the area in which r_l is statistically significant, an assumption is made that S_G is approximately equal to S_0. Thus, (4.1) becomes

$$B_G = r_l(B_0 - \bar{B}_0) + \bar{B}_G, \tag{4.3}$$

and the difference D between this estimate of B_G and the least-squares estimate from (4.2) is

$$D = r_l(1 - S_G/S_0)(B_0 - \bar{B}_0). \tag{4.4}$$

Furthermore, assuming a normal distribution of deviations $B_0 - \bar{B}_0$, not more than a 10% variation in standard deviation over the area of effective r_l, and an extreme deviation of $3S_0$ in $B_0 - \bar{B}_0$, then an extreme estimate of D is 0.3 $r_l S_0$. Thus, even if S_G differs significantly from S_0, D will not become large in the outer parts of the area of significant distance autocorrelation where r_l is small. Of course, this does not mean that the estimate of B_G is necessarily good, but only that it is near the best that can be obtained by using (4.2).

In the application to rainfall analysis the starting approximation has been generated using an approximation of the type (4.3). As the distribution of the correlation function was unknown, r_l was assumed to have the form $(R^2 - l^2)/(R^2 + l^2)$ and to be homogeneous over the analysis area. If sufficient information on the correlation function for required scale variations were available, separate values of r_l could be used with each iteration over an influence region defined by the significance of r_l. As well as combining the features of (4.3) with the Cressman type model in the initial approximation, the analysis procedure is modified, as described in the next section, to include changes in the scale of analysis according to the density of information.

5. A modification for information density

For the Cressman analysis scheme, the reduction in the pass radius from one iteration to the next may be made a function of the information density relating to that scale. In the absence of sufficient information on this relationship, a linear form

$$R' = R_1 - (R_1 - R)I/I_D \tag{5.1}$$

was assumed. Here R' is the modified iteration radius, R the iteration radius appropriate to the scale required to be analyzed, R_1 the radius appropriate to the largest scale analyzed, I the information density around the observation point, and I_D the information density in the densest data region. The analysis scheme, therefore, characteristically does not greatly reduce the scale of variations analyzed at each iteration in the sparse data regions.

In practice the information density modification factor I/I_D is evaluated at the end of an iteration and applied for the next. The series of distance weights computed at each grid point for all observations within a radius R of the grid point are summed and this becomes a convenient measure of the information density I. Thus, (5.1) becomes

$$R' = R_1 - (R_1 - R)\overline{\sum_1^N W_i} / \sum_1^N (W_i)_{\max}, \tag{5.2}$$

and only the factors $\overline{\sum_1^N W_i} / \sum_1^N (W_i)_{\max}$ need be saved for each grid point for each iteration. In the above $\overline{\sum_1^N W_i}$ is now the average of the sum of the accumulated distance weights at the four grid points surrounding an observation point and $\sum_1^N (W_i)_{\max}$ is the highest value of the sum of the weights over the analysis data region.

6. Filtering

The use of an information density modification involves a higher degree of implicit smoothing in the analysis scheme than does the standard Cressman scheme since in the very sparse data regions the areas of influence of observations are maintained as near as possible in an overlapping state during successive iterations. However, as indicated by Cressman (1959), and as demonstrated by Stephens (1967), around "data holes" the method cannot act as a sufficient smoother and, therefore, finally, some form of explicit smoothing is necessary to remove irregularities in these regions. For a fairly dense data network during analysis it is reasonable to apply a filter function of the type [see Shuman (1957)]

$$B_G' = B_G + 0.5\,\mu(1-\mu)(B_1 + B_2 + B_3 + B_4 - 4B_G) + 0.25\,\mu^2(B_5 + B_6 + B_7 + B_8 - 4B_G), \tag{6.1}$$

where B_G' is the smoothed value and B_G the original grid point value. The subscripts in the smoothing operator are identified in Fig. 1.

However, using a value of 0.5 for μ, the response of this filter (6.1) to harmonic waves of varying frequency indicates that although marked attenuation of the short waves results after several applications, the

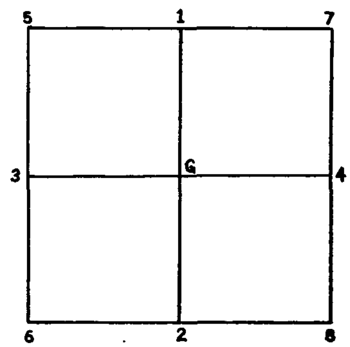

FIG. 1. Grid reference for definition of smoothing operators.

medium and long waves are also seriously damped. Thus, in sparse data regions, grid values unaffected by data during the analysis could be consistently smoothed with each application of this filter. This may be tolerable for the small scales of feature present in these sparse data regions, but is not so for the large-scale features. This effect may be avoided if the numerical filter is designed so as to have negligible influence on the longer wavelength variations of the analyzed pattern.

Wallington (1962) has devised a method for designing a filter with the desired characteristics. He uses elementary filters which eliminate selected wave components and restore the remaining required portion of the spectrum. If the function to be smoothed has values f_x at a point x and f_{x-d}, f_{x+d} at a distance d on either side, then the elementary filter,

$$f_x' = f_x + (a/2)(f_{x+d} + f_{x-d} - 2f_x),$$

changes the amplitude of a wave with wave number $k (k = 2\pi/L_k$, where L_k is the wavelength) by a factor

$$M_k = 1 - a(1 - \cos kd),$$

where f_x' is the smoothed function value and a is a coefficient governing the effect of the filter on different wavelengths. In smoothing two-dimensional fields the elementary filter is simply applied first in one coordinate direction and then in the other on the modified field. For n filtering operations Wallington shows the amplitude of a two-dimensional wave is reduced by a factor

$$M_{kj} = \prod_{r=1}^{n} [1 - a_r(1 - \cos kd)][1 - a_r(1 - \cos jd)], \quad (6.2)$$

where k and j are wave numbers of the pattern in each coordinate direction. However, it should be noted that the selective filter derived from solution of (6.2) may have pronounced directional properties. These are made obvious by expressing (6.2) in the form

$$M_{kj} = \prod_{r=1}^{n} \left[1 - a_r\left(1 - \cos\frac{2\pi \sin\theta d}{L}\right)\right] \times \left[1 - a_r\left(1 - \cos\frac{2\pi \cos\theta d}{L}\right)\right], \quad (6.3)$$

where θ is the wave-front orientation of the wave with wavelength L. The minimum value of magnification is seen to occur when $\theta = 45°$. The simple nine-point filter (6.1) has little wave orientation effect because its selectivity is poor; however, the more selective the filter becomes then the more pronounced are orientation effects for those wavelengths near the inflexion point of the frequency response curve.

In practice these orientation effects were almost completely eliminated by combining two filters, each having the same response characteristics, one applied in the grid coordinate directions and the other applied at 45° to the coordinates using the diagonal matrix of points spaced $\sqrt{2}d$ apart. Of course, the total reduction in unwanted wave amplitudes is now the product of the separate reductions of each filter and the burden of computing has increased by a factor of two.

In the development of the analysis model a single filter having the response shown in Fig. 2 may be

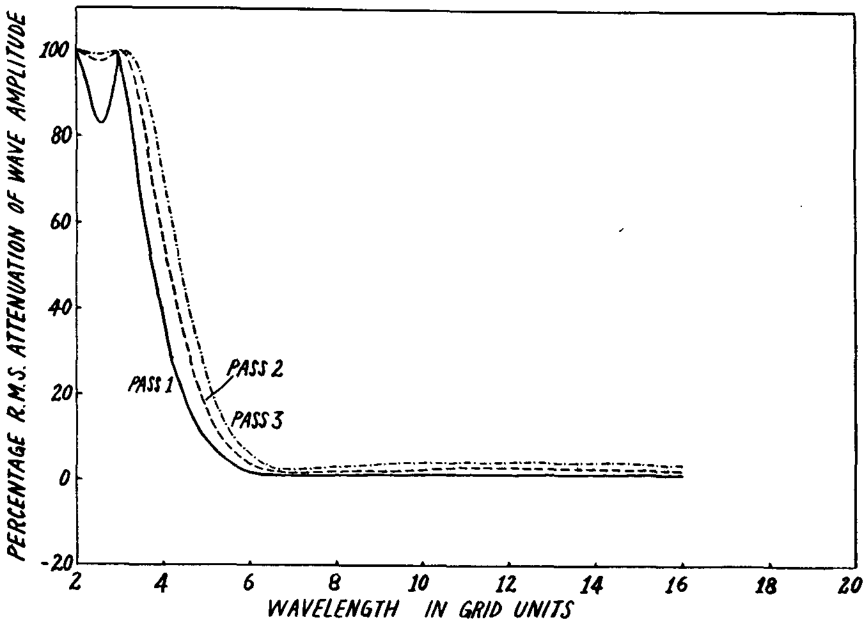

FIG. 2. Response curves for the magnification reduction filter used in the experiment. One-dimensional magnified and reduced values are B_G'' and B_G', respectively, where

$$B_G'' = 0.499B_{G_{-2}} - 2.457B_{G_{-1}} + 4.916B_{G_0} - 2.457B_{G_{+1}} + 0.499B_{G_{+2}},$$
$$B_G' = 0.083B_{G_{-2}} + 0.250B_{G_{-1}} + 0.333B_{G_0} + 0.250B_{G_{+1}} + 0.083B_{G_{+2}}.$$

applied to each successive approximation before commencing the next adjustment to the analysis. A filter having suitable response characteristics was derived by solving (6.2) for the values of a with four selected M_{kj} values, and the graph of the filter response as a function of wavelength is shown in Fig. 2.

7. Interpolation

In two-dimension analysis it is reasonable to expect that maximum and minimum points in the field will rarely coincide with grid points. If linear interpolation is used, maxima and minima would always be located at grid points so that at least a second-order interpolation formula is necessary to estimate their true positions realistically.

The Bessel interpolation formula,

$$f(x_0+F_x)=f_0+F_x(f_1-f_0)+F_x(F_x-1)(f_{-1}+f_2-f_0-f_1)/4, \quad (7.1)$$

was chosen, since terms involving odd order differences vanish and the residual interpolation error near the middle of the grid interval d is favorable (Berezin and Zhidkov, 1965). In (7.1) the function values f_n and f_{-n} are given at points x_0+nd and x_0-nd where n takes values 0, 1, -1, 2 and F_x is the fractional grid distance of the point of interpolation from x_0 in the positive x direction. In two dimensions, if the coordinates of the point where interpolation is required are x, y, then $x_0+F_x=x$ and similarly for the other coordinate $y_0+F_y=y$. In practice an interpolation was first made in the y direction for the four points (x_0, y), (x_0-d, y), (x_0+d, y) and (x_0+2d, y), and the value at the point (x, y) interpolated from the values at these four points.

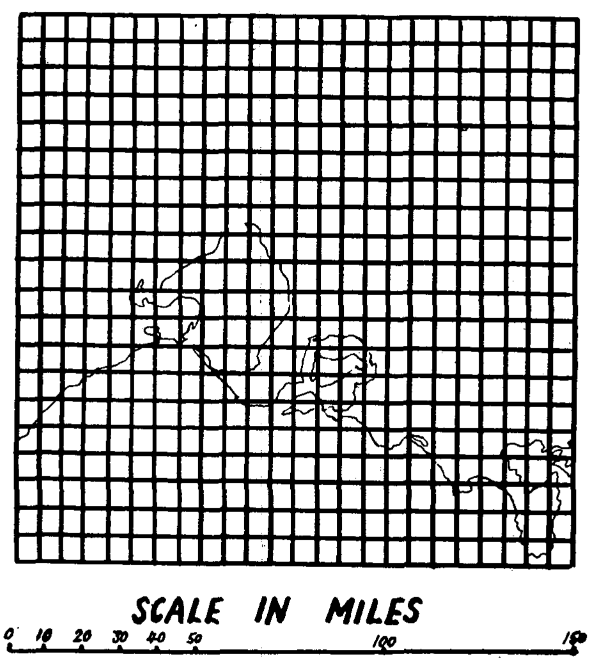

FIG. 3. Section of the 53×88 grid used for analysis.

8. Application to climatic normal rainfall analysis

In applying (4.3) to produce a starting approximation for monthly normal rainfall analyses, it was assumed that on the average the regression line for normal rainfall at one point with normal rainfall at another point within the region of significant distance correlation passes through the origin, i.e., $\bar{B}_G=r_l\bar{B}_0$. This enables the production of the starting approximation for (2.1) simply by use of the equation

$$^0B_G=\sum_{i=1}^{N} r_{l_i}(B_0)_i/\sum_{i=1}^{N} r_{l_i}, \quad (8.1)$$

where the summation is over the N stations within a distance R of the grid point, R being chosen so that at least one observation affects each grid point.

The computer program designed (see Appendix 1) caters for the input of the distribution r_l if this is available. However, in the monthly normal rainfall examples attempted here, the Cressman weighting function was applied, i.e., $r_l=W$ with the value of R set at eight grid units or approximately 80 n mi (148 km).

The months March, June and November were chosen as analysis examples so as to obtain a wide variation in the expected type of rainfall pattern. The basic data consisted of the normal rainfall data for Victorian climatological stations.

In the analysis of this data the starting approximation (see Fig. 4) was computed using (8.1) as described. A total number of 53×88 grid points covered the analysis area (see Fig. 3). A small grid spacing was dictated by the variability of rainfall, the spacing of 0.1 inch (6.3 km) in the x coordinate direction and 0.166 inch (10.1 km) in the y coordinate direction was used and corresponded, respectively, to the character and line resolution of the computer output. However, with incremental plotter output these restrictions are of course not necessary.

The analysis was then carried out using the modification for information density as given in (5.2) for the iteration radii R indicated in Table 1.

TABLE 1. Pass radii for monthly normal rainfall analyses and for monthly total rainfall analyses.

Pass no.	1	2	3	4	5	6
Pass radius (grid units)	7.0	5.0	4.0	3.0	2.0	1.0

As a measure of the accuracy of the analysis, Table 2 shows statistics of the deviation of the interpolated analysis values at the station locations from the observed data. Although with sparse data networks some filtering is desirable, no explicit filter was applied to the examples computed here because of the effect of the information density modification and the relatively high data density.

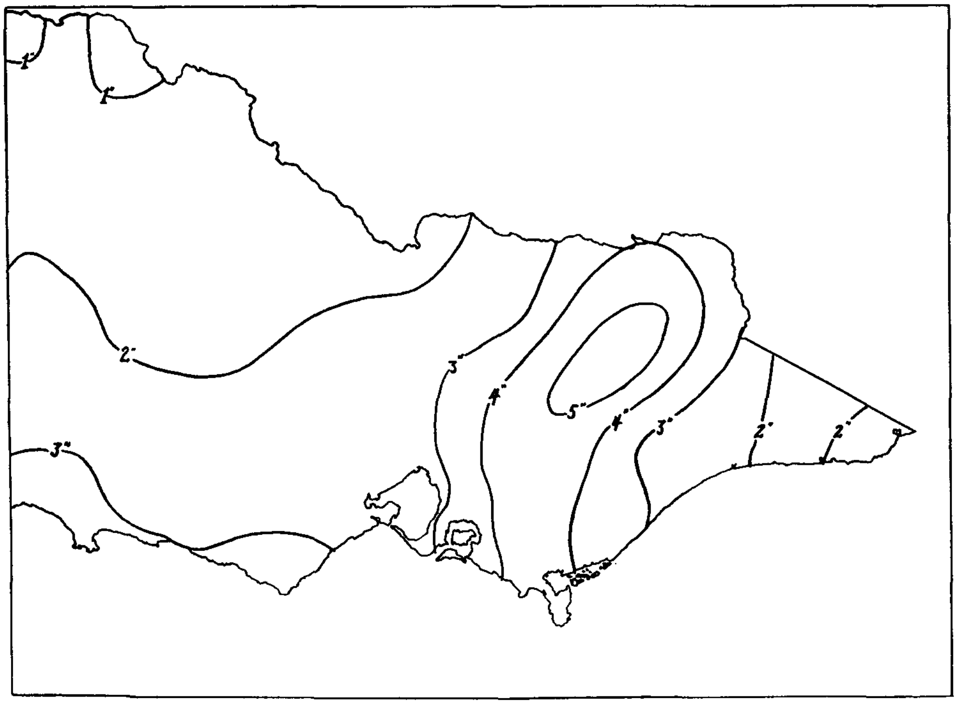

FIG. 4. The starting approximation for the analysis of June normal rainfall.

For comparison, the same data were processed without using the modification for information density. The resultant error statistics are given in Table 3, and indicate a slight improvement in the numerical fit of the observations. However, the pattern comparison of this objective analysis with the manual analysis revealed less favorable correspondence than when information density was used. Fig. 5 is the manual analysis of the June normal rainfall and Fig. 6 is the objective analysis using the information density modification. The other normal rainfall analyses have not been presented but Table 2 indicates their general accuracy. It will be noted that the main differences between the manual analyses (Fig. 5) and the objective analyses (Fig. 6) occur in northeast Victoria and this is due to the assumption during manual analysis, that the rainfall gradient is proportional to the gradient of topography (See Figs. 5 and 9).

9. Application to monthly total rainfall analysis

In dealing with monthly totals it was possible to use the approximation (4.3) to generate a starting approximation since the values of $\bar{B}_G$ and $\bar{B}_0$ were known from the analysis of the normal values.

The pass radii used for the monthly total rainfall analyses are set out in Table 1 and are identical with those used in the normal rainfall analyses. In the first trials the successive approximations were smoothed using one application of the magnification reduction filter whose response function appears in Fig. 2. However, a requirement that the isohyets fit the data

TABLE 2. Final pass statistics for analysis of monthly normal rainfall using the information density modification (1 point = 0.01 inch).

Analysis	Average error (points)	Standard deviation (points)	Mean deviation (points)	rms error (points)
June Normal	0.0	5.7	2.3	5.7
March Normal	0.0	3.7	1.5	3.7
November Normal	0.0	3.1	1.4	3.1

TABLE 3. Final pass statistics for analysis of monthly normal rainfall without the information density modification (1 point = 0.01 inch).

Analysis	Average error (points)	Standard deviation (points)	Mean deviation (points)	rms error (points)
June Normal	0.1	5.2	1.9	5.2
March Normal	0.0	3.4	1.3	3.4
November Normal	0.1	2.8	1.1	2.8

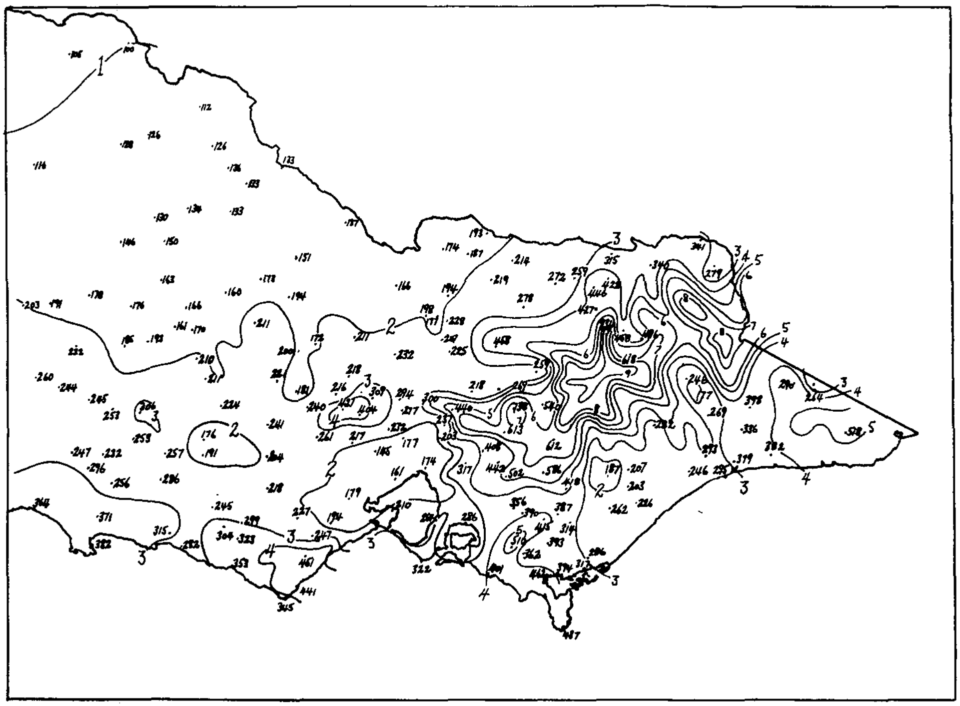

FIG. 5. Manual analysis of June normal rainfall data.

exactly demanded that explicit smoothing be eliminated. It should also be remembered that the minimum scale processed by the analysis system corresponds to a wavelength twice the last iteration radius and, therefore, any numerical filter used in conjunction with the analysis should not seriously attenuate waves of wavelength greater than $2R$.

Table 4 gives the statistics for the monthly total rainfall analyses and indicates that a consistently good final analysis has been obtained for each case. Manual

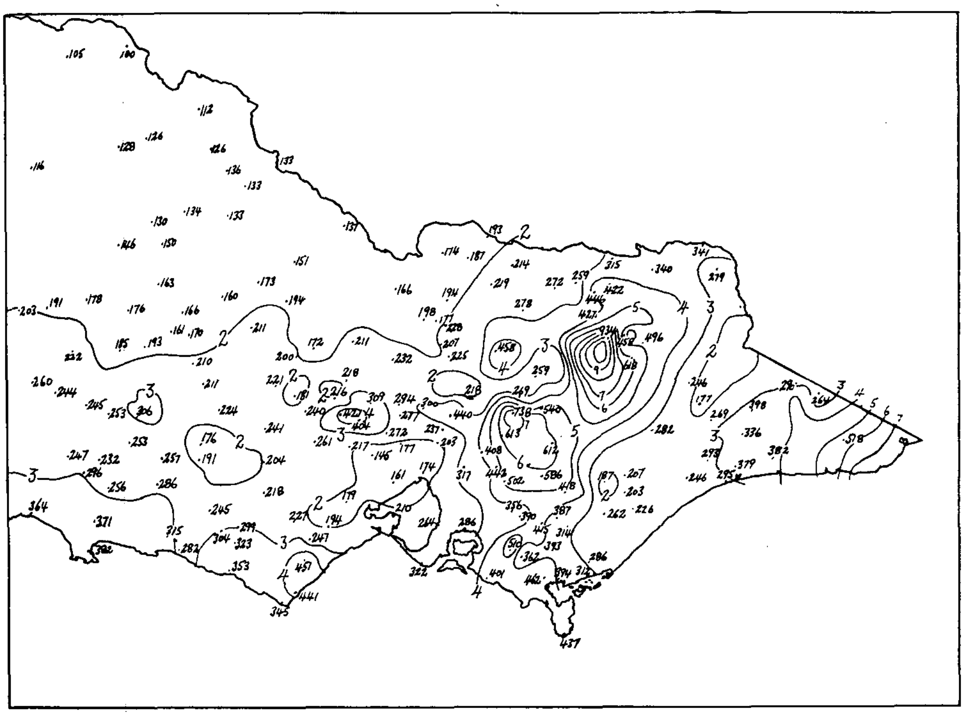

FIG. 6. Automatic analysis of June normal rainfall data.

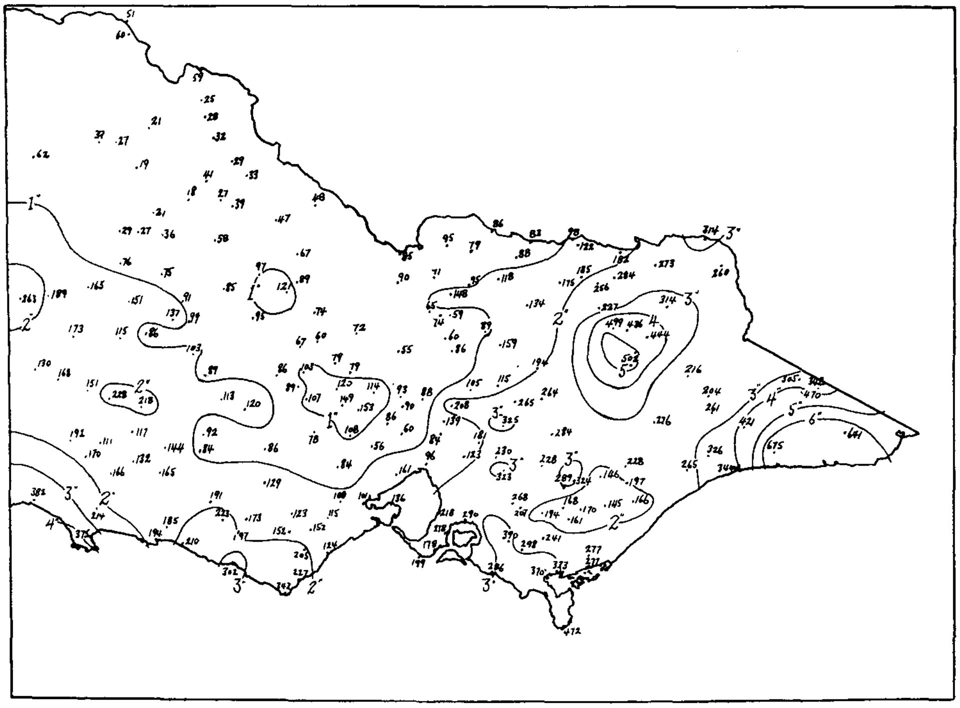

FIG. 7. Manual analysis of June total rainfall data.

and automatic versions of the June total rainfall analyses are presented in Fig. 7 and 8, while the final pass statistics for the analysis of monthly total rainfall without the information density modification are shown in Table 5.

10. Other applications of the analysis method

In the analysis of normal and monthly totals of rainfall any orographic effects should be of fairly large scale and able to be directly established from the data. Although comparison of the analyses in Figs. 5 and 6

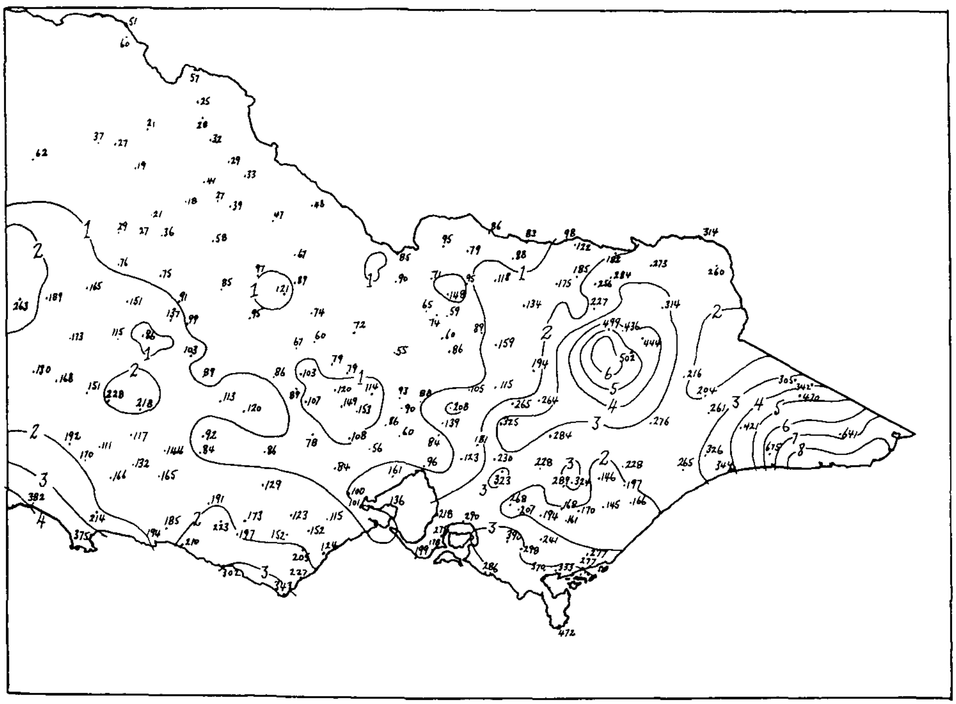

FIG. 8. Automatic analysis of June total rainfall data.

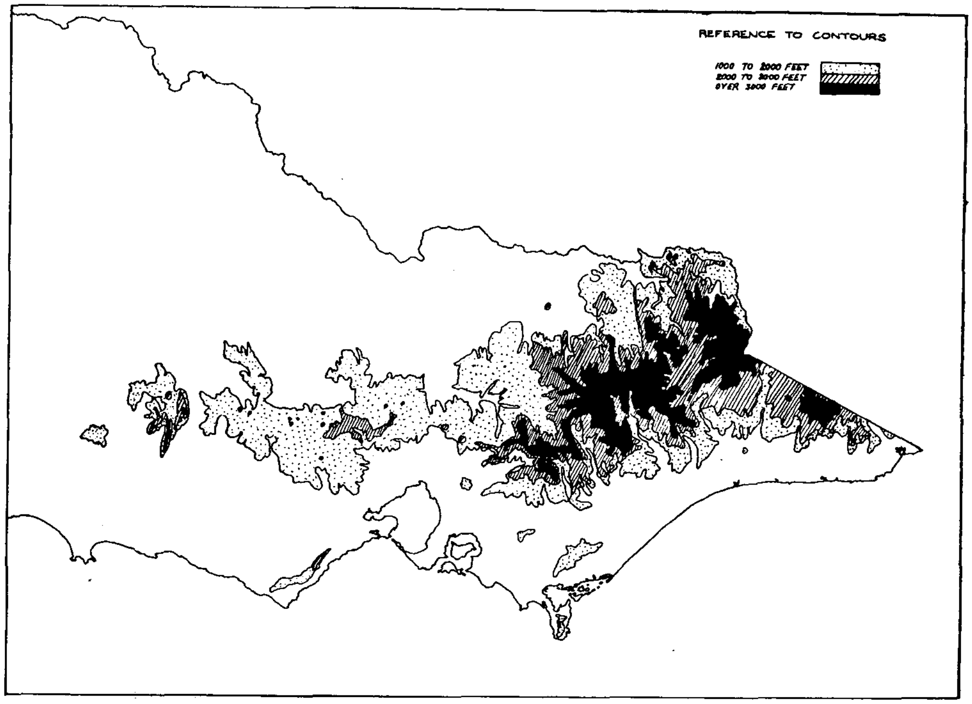

FIG. 9. Topographic chart of Victoria.

does not appear to support this contention, especially in northeastern Victoria, this is probably because not all possible rainfall stations were used in the analyses of Figs. 5 and 6. However, it is considered possible to use the analysis procedure for hydrological purposes in the analysis of storm period rainfall or perhaps daily rainfall when smaller scale orographic effects may be present. For such analysis it would be necessary, especially with variable density of data, to incorporate some orographic effects. Also, since short period rainfalls are discontinuous in space at zero rainfall, the starting approximation would be more appropriately given by (8.1), on the assumption now, that $\bar{B}_0=\bar{B}_G=0$ in (4.3).

The following approach to the analysis of storm period rainfall totals may be of some value in hydrological studies. For a storm period during which the wind flow is from the same general direction, a relationship of the form $\nabla\rho=\alpha(\nabla Z)_v$ might be assumed. Here $\nabla\rho$ is the rainfall gradient, α a proportionately factor and $(\nabla Z)_v$ the gradient of the height Z of the earth's surface in the direction of the mean wind. For rainfall variations whose scale is governed by orography, a modified estimate of the grid point values is given by

$$^{P}B_G' = {}^{P}B_G + \gamma \sum_1^N W_i(B_0 + \mathbf{l}\cdot\alpha(\nabla z)_v - {}^{P}B_G)_i / \sum_1^N W_i, \tag{10.1}$$

where γ is an arbitrary relative weighting factor reflecting the degree of orographic influence desired in the analysis, $^{P}B_G$ is given by

$$^{P}B_G = {}^{(P-1)}B_G + \sum_{i=1}^{N} W_i(B_0 - B_I)_i / \sum W_i,$$

and B_I is the value of B interpolated at the observation point in the grid value field B_G.

The analysis method using the information density modification and a first approximation of the type (8.1) has been applied with some success in accurate analysis of ground contour values from original survey heights for drainage studies. In this application the area of

TABLE 4. Final pass statistics for analysis of monthly total rainfall using the information density modification.

Analysis	Average error (points)	Standard deviation (points)	Mean deviation (points)	rms error (points)
June 1966	0.1	2.9	1.5	2.9
March 1966	0.2	4.1	2.1	4.1
November 1966	0.0	4.0	2.2	4.0

TABLE 5. Final pass statistics for analysis of monthly total rainfall without the information density modification.

Analysis	Average error (points)	Standard deviation (points)	Mean deviation (points)	rms error (points)
June 1966	0.0	2.6	1.1	2.6
March 1966	0.0	3.6	1.6	3.6
November 1966	0.0	3.5	1.7	3.5

analysis was only a few square miles and the range of contour values only about 100 ft; however, the automatic analysis compared satisfactorily with an acceptable manual analysis.

The modified analysis method has been introduced into an Australian region operational differential analysis scheme and has been specifically applied to isobaric surface, contour, isotach, isotherm, dew point, temperature, and wind-component analyses. Although the data density is sparse, and accurate analyses are not possible, the method has produced acceptable results which compare well with manual analyses.

11. Conclusions

The modification to the Cressman procedure involving information density, dependent-distance weighting functions and preparation of the first approximation, using a small mesh size, has been applied to the analysis of certain kinds of rainfall data.

The scope of application of the analysis method has been extended beyond the usual synoptic-scale analysis of meteorological parameters, and has included also topographic analysis for engineering purposes.

Acknowledgments. The determination and testing of

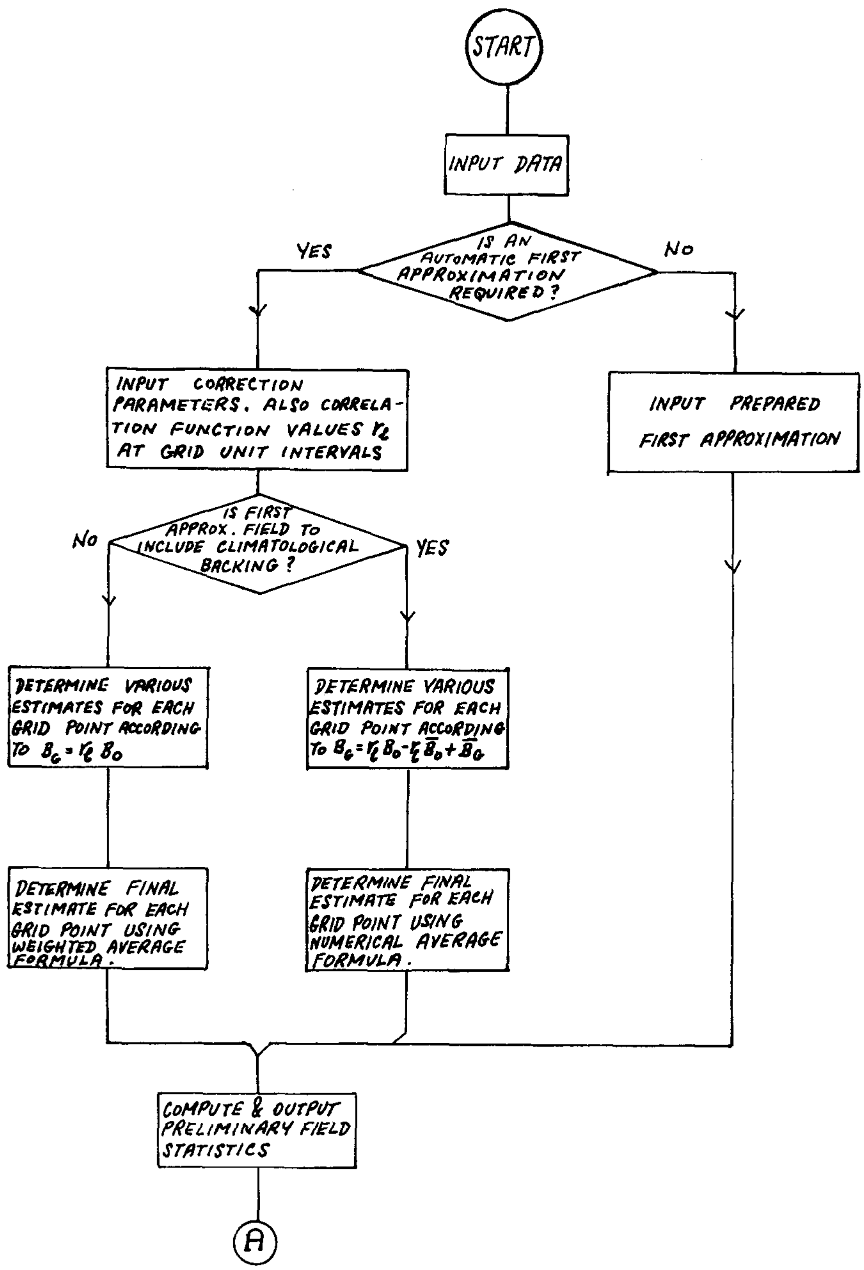

FIG. 10a. Operations flowchart for the preparation of a starting approximation to the analysis. (FIG. 10b continued on p. 28.)

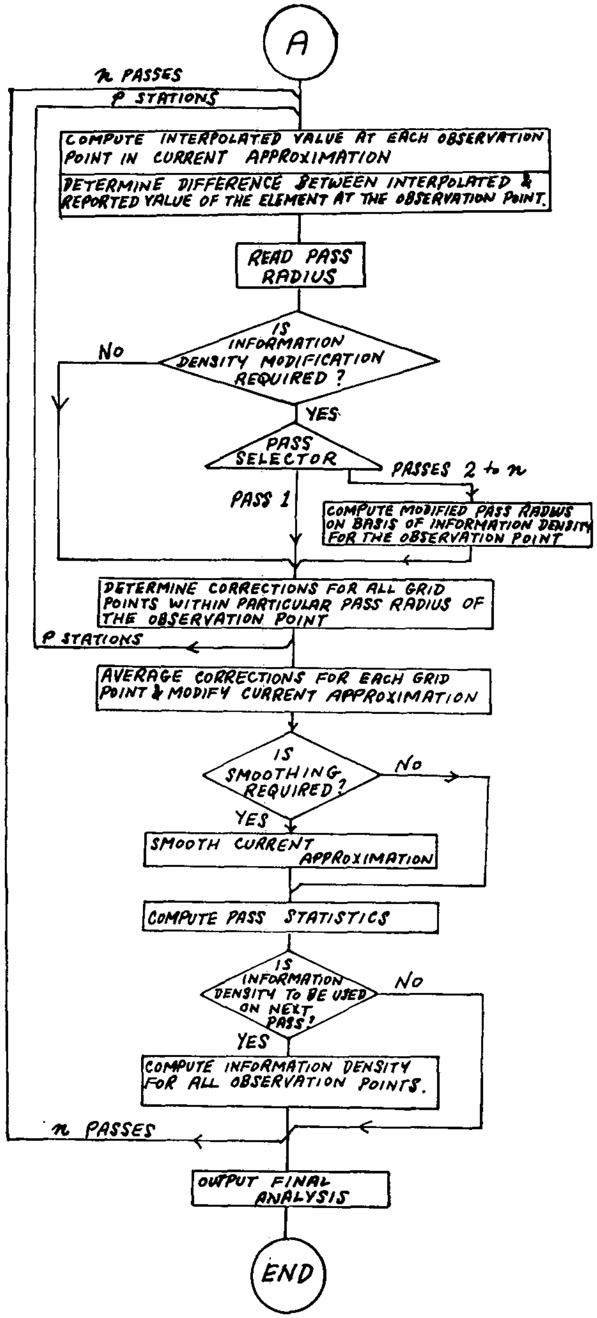

FIG. 10b. Operations flowchart for the analysis procedure.

the filter whose characteristics are given in Fig. 2 was carried out by Mr. R. S. Seaman of the Commonwealth Bureau of Meteorology, Melbourne. The figures were drafted by Mr. R. Weinert. Mr. A. Muffatti of the Central Office Weather Records and Statistics Section analyzed the limited normal rainfall presented in Fig. 5. Mr. S. Guliano of the Victorian Regional Office analyzed the rainfall data of Fig. 7.

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APPENDIX

This appendix contains the details of the program actually designed for the analysis of scalar variables.

Flow charts of the operational procedures involved in the preparation of a starting approximation and in the analysis routine itself are shown in Figs. 10a and 10b, respectively. The flexibility of the program is improved by incorporating several possible options into these procedures. Thus, in the preparation of a starting approximation, provision has been made for the input of a specially prepared field or, alternatively, for the computation of this field on the basis of input data. In the analysis procedure itself, important optional facilities are incorporated for the use of information density and smoothing.

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