CLIMATOLOGY

THE INTERPOLATION OF GRIDDED CLIMATIC DATA FOR USE IN CLIMATIC CLASSIFICATION SCHEMES

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ABSTRACT

A method of spatial interpolation for gridded climatic data using the distance-weighted-average of adjacent stations with similar elevation is proposed for use with climatic classification schemes. To determine the optimal number of stations for interpolation, a procedure was developed in which the differences between known data, at a randomly selected network of grids, and data averaged from the closest one through six stations were minimized. Limits ranging from 100 to 1000 m, in increments of 100 m, were also imposed on the difference in elevation between the adjacent stations and each random grid. The station-elevation combination which resulted in the smallest difference between the actual and interpolated value for each of the climatological variables tested was considered appropriate for the actual interpolation. An example of the use of this technique with a climatic classification of plant hardiness is also discussed.

For most variables, the differences resulting from interpolation were generally small. This was especially true for variables such as monthly temperature and precipitation. Differences averaged 0.7° C for maximum temperature and 5.8 mm for precipitation. Monthly differences for wind speed and sunshine averaged 2.5 km/hr and 4.0 hr, respectively. The interpolation difference for annual snowfall was high, averaging 37 cm.

1. INTRODUCTION

Climatic stations tend to be located in areas of human settlement. Therefore, climatic data are often sparse in desert, mountain and polar regions. The opposite is true in population centers where dense groupings of data exist. Such a problem is often compounded by the widely spaced network of stations recording such meteorological variables as sunshine. Since this spatial irregularity of climatological data often presents problems when such data is used to classify climatically similar regions, a simple, yet accurate, method of spatial data interpolation would be advantageous.

Although several researchers have suggested methods for the spatial interpolation of data, no one method has been widely accepted. In general, interpolation methods fall into three categories. Weighted interpolation is based on the assumption that interpolated values can be expressed as some weighted-average of existing data at adjacent sites. Cressman (3) used this method, with inverse squared distance as a weighting factor, to interpolate height contours. In addition, Cressman used a factor which caused the weighting to equal zero beyond some given distance. Similar weighted interpolation techniques have been proposed by several authors including Sheppard (4) and MacCracken and Sauter (5).

Interpolation can also be accomplished by fitting a least-squares polynomial to existing data such that the goodness of fit is minimized. This procedure can be applied to an entire grid network or over a specific region influenced by only a few stations (6). Akima (7) used fifth degree polynomials to interpolate values in triangular cells having observed values at each vertex. The solution of each polynomial required the determination of 29 coefficients.

Optimum interpolation was developed by Gandin (8). This technique uses statistical properties of the data, such as covariances, to formulate an interpolation function. Therefore, the past behavior of a given meteorological field of data forms the basis for interpolation. Optimum interpolation is particularly suited for the interpolation of synoptic-scale data used to initialize circulation models.

Generally, the meteorological applications of the above interpolation techniques have been for weather map analysis, the initialization of circulation and air pollution transport models and modeling certain atmospheric processes. Although it appears that spatial data interpolation would be advantageous to statistical climatic classification schemes and homoclime analyses, at present its application in these areas is limited.

Booth *et al.* (9) appear to be the only authors to use spatial data interpolation to analyze regions with similar climates. They developed a method of homoclime analysis which compared the climate of a target location with conditions interpolated at sites in a regular grid. As an example of this method, Booth *et al.* (9) compared target locations in Africa and South America with 2795 Australian sites in a half-degree latitude-longitude grid. At each grid site, 18 temperature and precipitation variables were interpolated using a technique developed by Wahba and Wendelberger (10). The technique used splines and generalized cross validation (GCV) to estimate these variables from the sites' latitude, longitude and elevation.

Spline interpolation is designed to fit a surface of minimum curvature to a network of observations. Such a procedure is an improvement over polynomial regression since the oscillatory tendency of high-degree polynomials often restricts their use, especially when approximating natural functions. Also, polynomial models tend to induce large fluctuations over the entire data range, when fluctuations may occur only over small portions of the range.

Generalized cross validation (GCV) is a procedure which can be used in conjunction with splines and is designed to minimize the mean square residual errors resulting from the spline interpolation. The GCV is calculated for a spline surface by removing each data point and determining how well the remaining data predict the omitted value. Both the use of splines and GCV are described in detail by Wahba and Wendelberger (10).

According to Booth *et al.* (9), the spline interpolation used in their study had "acceptable levels of accuracy." Mean maximum and minimum temperatures were estimated with mean errors of 1.3 and 4.1%, respectively. The mean errors associated with monthly precipitation were generally below 10%.

Although numerous other studies have isolated homoclimes and developed climatic classifications (11, 12, 13), none have utilized a grid or attempted to interpolate observations in data sparse regions. Instead, these studies have simply used data at individual stations and relied on freehand interpolation to define boundaries between different climatic regions.

Despite the wide variation of climatic conditions that may occur within a grid, a gridding scheme is advantageous for isolating the general pattern of climatically similar regions. Also, when a large number of individual stations are used in such analyses, gridding reduces the vast amount of computer memory required for statistical classification. In addition, the use of an interpolation technique in data sparse areas, strengthens the significance of climatic boundaries which otherwise would be arbitrarily placed by freehand interpolation.

In this paper, a method of spatial data interpolation using distance-weighted-averages of data from adjacent stations meeting certain elevation restrictions is proposed for use with statistical climatic classification techniques. Although such a procedure assumes that meteorological parameters vary linearly with horizontal distance and remain constant within certain ranges in elevation, it provides a relatively simple and sufficiently accurate method of interpolating gridded climatic data for use in such studies. To illustrate this technique's usefulness with climatic classification schemes, a study by DeGaetano and Shulman (14) in which regions of the U.S. and Canada were classified with respect to plant hardiness is discussed.

2. DATA

The availability of climatic data varies markedly across the United States and Canada. For variables such as temperature and precipitation, a relatively dense network of data exists. However, areas of sparse data occur in the Rocky Mountains, desert southwest and polar regions. Figure 1 shows the distribution of stations recording current 30 year temperature, precipitation and degree-day normals. Bases of 1.7° C and 10.0° C were used to calculate the monthly heating degree-days (HDD) and growing degree-days (GDD), respectively. These bases were used by DeGaetano (15) because of their relationship to plant hardiness. Thirty-year average freeze dates are available at a network of stations similar to that of the temperature and precipitation data.

Except for extreme temperatures, few stations, especially in Canada, have 30 year records for the remaining variables used in DeGaetano and Shulman's hardiness classification. A record length of 19 years was used for these data since provided an adequate number of stations and did not significantly compromise the statistical qualities of the data.

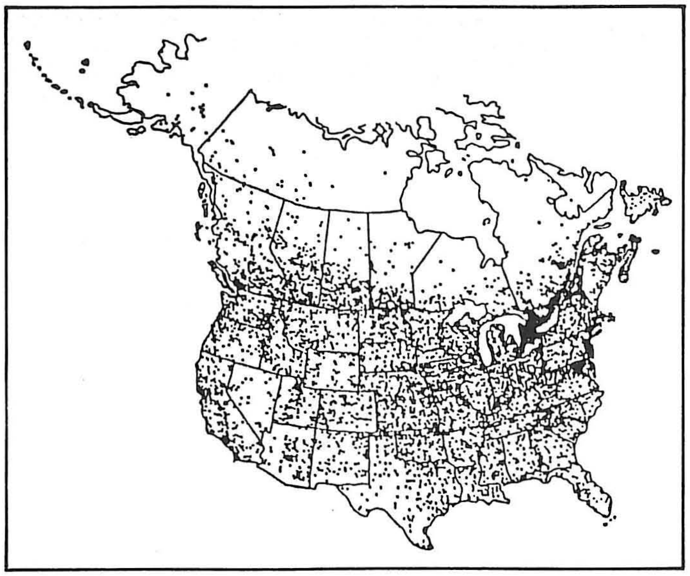

Fig. 1. Stations reporting temperature, precipitation and degree-day data.

These climatic variables are also observed over a wider spaced network of stations. Figure 2 shows the distribution of stations reporting at least 19 years of sunshine observations. The spatial distribution of stations reporting at least 19 years of monthly wind speed, relative humidity, extreme maximum and minimum temperature and annual snowfall observations is similar with the exception of the temperature extremes and snowfall which are recorded at many additional southern Canadian locations.

The above data were placed into a grid devised by DeGaetano (15), which divided the United States and Canada

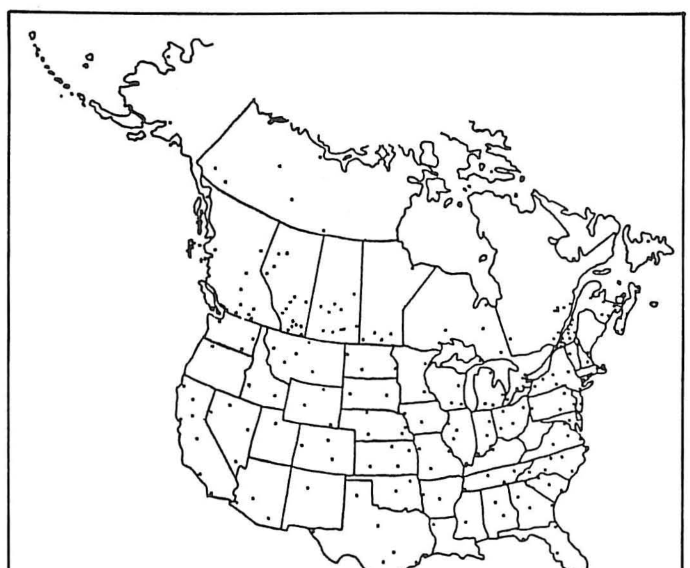

Fig. 2. Stations recording sunshine data.

into 1234 grid boxes. South of 49°N, the grids' dimensions were one degree of latitude by one degree of longitude measured at 45°N. North of 49°N, the size of the grids ranged from double these dimensions to as large as 5 times the southern grids' size as a function of data sparsity. Since longitudinal distance varies with latitude, it was necessary to measure this distance at a fixed latitude to prevent the distortion of the nothernmost grid boxes.

Grid box averages for each climatic variable were calculated by averaging their values over all stations within each grid. This gridding scheme provided a useful method for identifying large-scale areas that are climatically similar, albeit at the expense of eliminating differences within the grid boxes. A similar grid was used by Booth *et al.* (9) in their comparison of climatic conditions in Australia with those of regions in Africa and South America. Rind (16) also used a comparable grid to classify vegetation types and calculate water storage capacities in a general circulation model.

3. DISTANCE-WEIGHTED-AVERAGE PROCEDURE

Due to the distribution of climatological data, it is likely that the application of such a gridding scheme would result in a number of grid boxes without any stations. To eliminate this problem, a method is needed to interpolate data in empty grids, thereby producing a continuous data set. Such a method was devised using distance-weighted-averages. This method assumes that climatological variables vary smoothly with horizontal distance. When used with gridded data, this assumption results in fairly accurate interpolation, especially when adjacent stations are fairly close, since grid averages tend to suppress the variance exhibited by individual observations. Limits were placed on the differences in elevation between the grid cell and the stations used to further refine the interpolation.

Before such averages could be computed, the distances between the center point of the grid box and the n closest stations within some elevation difference range were determined. These distances were then used to derive the weighted-averages by the following formula:

$$R_N = \left[\sum_{i=1}^{n} V_i/D_i \right] / \left[\sum_{i=1}^{n} 1/D_i \right] \quad (1)$$

where

n is the number of stations used
R_N is the interpolated value
D_i is the distance to the ith station
V_i is the actual value of the variable at the ith station.

If only the closest station is used in the interpolation, equation 1 reduces to:

$$R_1 = V_1 \quad (2)$$

or the interpolated value is simply equal to the value at the closest station.

The optimal number of stations to use in such a interpolation procedure was not known *a priori*. Therefore, existing data at randomly chosen grids were interpolated using the closest one through six stations to the center point of each grid and ten elevation differences limits ranging from 100 to 1000 m in increments of 100 m. Since the choice of these limits was arbitrary, the results were compared to those of a trial using the closest 10 stations and 50 m elevation increments. However, these more stringent limits did not produce more accurate results.

Since the number of stations necessary for optimal interpolation could be a function of the particular variable, 75 grid boxes with data were randomly chosen from the population of 1234 grids to test each variable. The data for these grids were assuming missing and interpolated by the method outlined. For each of the 75 grid boxes, the monthly variables were interpolated using the closest one to six stations and each of 10 elevation ranges and a comparison of differences between the actual and interpolated values was made. Sixty weighted-averages were calculated during each month for each grid.

The choice of 75 random grids to determine the station-elevation combination appropriate for use in the interpolation was also arbitrary. Since the grid boxes were randomly chosen, it could be assumed that the differences from the actual values were also random and, by the central limit theorem, thirty grids should have been sufficient. To confirm this, the differences in the annual mean base 1.7° C HDD for 10 randomly chosen station-elevation combinations were plotted against a various number of randomly selected grids for which the data had been interpolated. For clarity, only six of the ten combinations are shown in Figure 3. The distribution of differences seems random with respect to grid number, however, a sharp decrease in the variability of the differences occurred with 40 or more grids. This suggests that the use of any number of grids above 40 would have been adequate. Therefore, the arbitrary selection of 75 grids was justified.

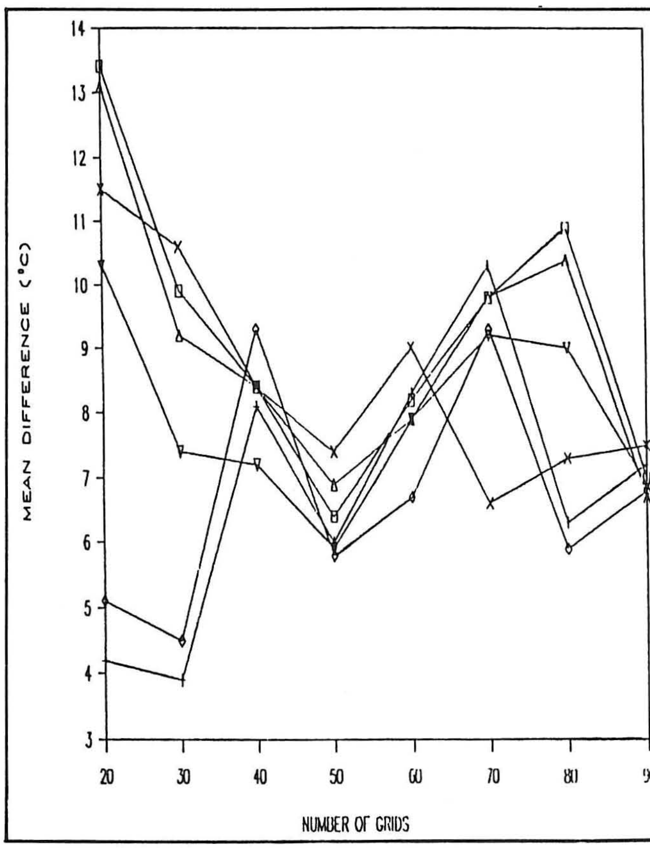

Fig. 3. Mean difference versus the number of grid boxes used to interpolate base 1.7° C HHD data for six random station-elevation combinations.

4. RESULTS

The interpolated values were compared to the actual values by calculating the mean absolute differences and standard deviations for each of the 60 station-elevation combinations. An example of these comparisons using maximum temperature is given in Table 1. Differences and standard deviations tended to be relatively large when only one or two stations or a large range in elevation was used. Relatively large differences and standard deviations also resulted when a small elevation range was used, since many of the closest stations did not meet such a strict elevation requirement. As the number of stations used became large, interpolation differences also tended to increase, since greater distances between the stations and interpolation site existed.

For maximum temperature, the smallest differences and standard deviations were generally associated with combinations consisting of between two and five stations within 200–400 m of the interpolation site's elevation. The smallest average difference and standard deviation for maximum temperature, 0.7° C and 0.8° C, respectively, occurred when the closest two or three stations within 300–400 m in elevation of the interpolated grid were used.

The magnitude of the differences which resulted from the interpolation procedure also depended upon the variable being considered. For variables observed in a relatively dense network of reporting stations, interpolation differences were generally small. Interpolation differences for variables observed over a more widely spaced network of stations were relatively small for sunshine and fairly large for snowfall. For each variable, the lowest mean absolute difference and standard deviation for the 60 station-elevation combinations tested is given in Table 2. Each mean was calculated using 900 values corresponding to 12 monthly differences at each of the 75 random grids. If the smallest mean difference and standard deviation occurred for more than one station-elevation combination, the combination with the fewest stations and greatest elevation range is given in Table 2. This combination was the simplest, computationally.

In general the magnitude of the differences was a function of the particular variable, topography and microclimatology. The lowest mean difference for maximum temperature, as expected, was less than that of minimum temperature, due to the decreased influence of microclimatic effects (Table 2). Microclimate was also a factor in that the smallest difference for maximum temperature occurred at several station-elevation combinations as opposed to that of minimum temperature which occurred at a unique combination. Although the HDD and GDD data were derived from both maximum and minimum temperatures, the smallest interpolation differences occurred using station-elevation combinations similar to that which produced the smallest minimum temperature interpolation difference. This similarity was most likely due to coincidence and not directly related to microclimatic effects.

In Table 2, the station-elevation combinations which resulted in the minimum interpolation differences for extreme maximum and minimum temperature seem to contradict microclimatic reasoning. The six closest stations and a relatively large elevation difference criterion produced the smallest interpolation difference for extreme minimum temperature. This may result from the fact that the network of extreme temperature stations was considerably less dense than that of the mean temperature stations. Therefore, the interpolation of these values may have been affected by synoptic rather than microscale features.

The importance of topography as a factor in the occurrence of freezes is illustrated by the small elevation difference range which corresponded to the minimum interpolation difference for both the last spring and first fall freeze dates (Table 2). Although the smallest mean difference for the fall date was one day greater than that of the spring date, both occurred when the same station-elevation combination was used.

Snowfall is highly affected by elevation. Therefore, the smallest interpolation difference for this variable also occurred using a small elevation difference range (Table 2). Since annual rather than monthly snowfall data were used, the mean differences were calculated using only 75 values, one for each random grid box. The large difference for snowfall, greater than 37 cm, resulted from the high variability in snowfall between neighboring stations and the sparsity of the network of snowfall stations. Due to the small number of stations, the closest snowfall station may have been located far from the interpolation grid, especially when the strict elevation difference criterion was imposed.

Since a large elevation difference range and a small number of adjacent stations were associated with the minimum interpolation difference for precipitation, station proximity was apparently of more importance than elevation (Table 2). This has some meteorological basis since, although precipitation is affected by elevation, its spatial variability can be great particularly in convective events.

Table 1. Mean absolute differences (upper value) and standard deviations (lower value) resulting from the comparison of known monthly maximum temperature data, at a randomly selected network of grids, with the distance-weighted-average interpolation of these data using the closest one through six stations and elevation difference limits ranging from 100 to 1000 m.

Stations	100	200	300	400	500	600	700	800	900	1000
1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
	1.1	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2	0.8	0.8	0.7	0.8	0.8	0.8	0.8	0.8	0.9	0.9
	1.0	0.9	0.8	0.9	0.9	0.9	0.9	0.9	1.0	1.0
3	0.9	0.8	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8
	1.1	0.9	0.8	0.8	0.9	0.9	0.9	1.0	1.0	1.0
4	0.8	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8
	1.2	0.9	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0
5	0.8	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8
	1.3	1.0	1.0	0.9	1.0	1.0	1.0	1.1	1.1	1.1
6	0.8	0.7	0.8	0.7	0.8	0.8	0.8	0.8	0.8	0.8
	1.3	1.1	1.1	1.0	1.0	1.1	1.1	1.1	1.1	1.1

Table 2. Number of stations and maximum difference in elevation (meters) between the interpolated grid box and those stations used to interpolate each parameter with minimum difference. The values of the average minimum difference and standard deviation for 75 grid boxes are also given.

Parameter	Number of Stations	Maximum Elevation Difference	Minimum Interpolation Difference	Standard Deviation
Maximum Temperature	2	300	0.7° C	0.8° C
Minimum Temperature	3	400	1.0° C	1.2° C
Precipitation	2	600	5.8 mm	8.4 mm
Snowfall	3	100	37.2 cm	64.8 cm
Extreme Max. Temperature	4	200	1.9° C	2.1° C
Extreme Min. Temperature	6	500	3.1° C	3.5° C
Wind Speed	4	600	2.5 km/hr	5.3 km/hr
Sunshine	2	500	4.0 hr	3.8 hr
Last Spring Freeze	5	100	8.3 days	9.2 days
First Fall Freeze	5	100	9.3 days	12.6 days
Relative Humidity	3	500	1.8 %	2.9 %
Heating Degree-Days	3	400	7.8° C	17.8° C
Growing Degree-Days	5	200	8.3° C	13.3° C

No strong meteorological bases were apparent for the station-elevation combinations which resulted in the minimum interpolation differences for wind speed, sunshine or relative humidity.

Figure 4 shows a climatic classification of plant hardiness developed by DeGaetano and Shulman (14) which used the distance-weighted-average technique to interpolate values in data void grids. In the United States, southern Quebec and the southern Maritime Provinces, each character approximates a grid box. Since the grid size was increased in the remainder of Canada and Alaska, the number of characters which defined a grid also increased. In the northernmost sections, a grid is approximated by 45 characters. For variables such as sunshine and wind speed, interpolation was required for approximately 75% of the 1234 grid boxes. Grid box averages of mean temperature and precipitation were interpolated for about 10% of the grids. These grids are indicated by the outlined areas in Figure 4. Since the interpolation of variables such as sunshine and wind speed was required for the majority of the grids, only the grids for which temperature and precipitation was interpolated are indicated in the figure.

Using the statistical analyses outlined by DeGaetano and Shulman (14), the 1234 actual and interpolated grid boxes were grouped into 23 distinct clusters which were climatically similar with respect to plant hardiness. Each of these clusters is shown by a unique symbol in Figure 4.

Generally, interpolated grid boxes were homogeneously distributed among the clusters. In the majority of cases, the interpolated grids were clustered with adjacent grids having actual data. Two notable exceptions occurred in the Great Lakes Region. Interpolated grids within the "S" and "=" clusters were clustered with the "." and "/" clusters, respectively. Although no strong argument could be made for including the grid in the "." cluster, the maritime effects associated with the Great Lakes may have influenced the climate of the grid clustered with the maritime "/" cluster.

To further analyze the interpolated grids with respect to the clusters in which they were grouped, the values of the components within each interpolated grid were compared to those of the other grids. Figure 5 shows a plot of the percent of component values from interpolated grids which were in each percentile of total within-cluster component values. For clusters which included interpolated grids, the component values were grouped into 10 percentiles and a count made of the number of component values from interpolated grids which fell into each percentile. As an example, Figure 5 shows approximately 39% of the component 1 values from interpolated grids were in the 40th percentile of all component 1 values considered. Likewise, 50% of the component 2 values lay in the 40th percentile. Using Figure 5, it was apparent that a similar percentage of interpolated and actual values were in each percentile. Therefore, within each cluster, the interpolated values were not biased toward high or low component values.

Fig. 4. Plant hardiness classification developed by DeGaetano and Shulman (14). Each symbol denotes a unique hardiness cluster. Grids with interpolated temperature and precipitation averages are outlined.

5. CONCLUSIONS

Based on the results presented in Table 2, the inverse distance-weighted-average interpolation procedure worked well especially for monthly maximum and minimum temperature, precipitation, GDD, HDD and annual freeze dates. Since a large number of stations with these data existed, the missing data could be interpolated using stations which were relatively close and within the selected elevation limits. The remaining variables were recorded only at a few widely spaced stations. Therefore, the stations used for interpolation were often located relatively far from the interpolated grid and thus the differences resulting from interpolation for these variables were generally higher.

Figure 4 shows that, in general, the interpolated grids were clustered with adjacent grids for which data was available allowing distinct, climatically similar clusters to be defined. Only 2% of the interpolated grids did not border a grid from the same cluster. While this was expected, since data from adjacent grids were used for interpolation, the distribution of interpolated values among the actual values within each cluster was significant. Generally, component values from interpolated grids were evenly distributed throughout each cluster's range of values (Fig. 5). This indicated that, after clustering, grid values interpolated with the distance-weighted average procedure were not biased toward the highest or lowest values within a cluster. This is especially important since any high or low bias of the interpolated values could have led to the formation of erroneous clusters.

Although Booth *et al.*, (9) achieved a similar representation of regional climate variation with grid values interpolated using splines and generalized cross validation, the distance-weighted-average procedure appears to be a much simpler alternative for such applications. Once the optimum station-elevation combination for each variable has been determined,

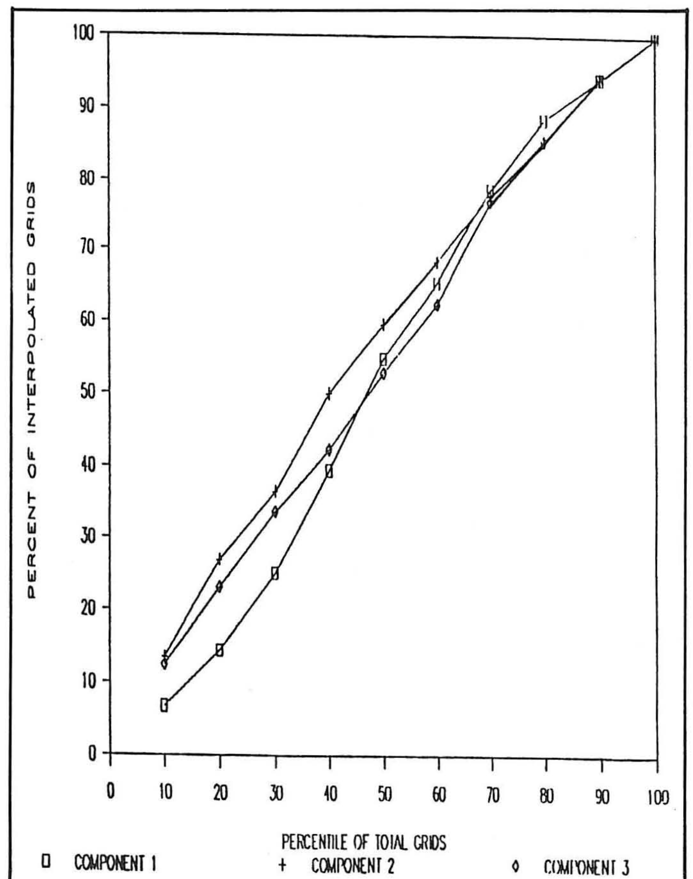

Fig. 5. Percent of component values from interpolated grids in each percentile of total within-cluster component values.

interpolation requires only a few comparatively simple calculations.

Albeit a variety of interpolation procedures including that used by Booth *et al.* (9), are more complex and applicable in many meteorological applications, the distance-weighted-average interpolation of gridded data seems appropriate for use with climatic classification schemes. In this application, the use of grid box averages tends to suppress the variance of the data and therefore enhances the efficiency of the less complex interpolation technique. Also, the inaccuracies inherent with the weighted-average method are further reduced once the interpolated data is subjected to principal component analysis and therefore are of little consequence. This, combined with the method's simplicity, makes the distance-weighted-average interpolation procedure well suited for use with such classification schemes.

When statistical procedures such as clustering are used to isolate climatically similar regions, a complete data set facilitates the analysis. Also, without interpolated data, the identification of climatic boundaries in data sparse regions is not possible. These factors, in conjunction with the distance-weighted-average method's ability to represent the regional-scale variations in climate with a few simple calculations, make the procedure advantageous despite its shortcomings.

Since the distance-weighted-average procedure is used only with grids having dimensions of $1° \times 1°$ or larger in the example, further analysis is required before the interpolation procedure can be applied to smaller grids. It is possible that the increased variability associated with smaller grids may result in a substantial loss of accuracy. In such cases, the use of a different weighting factor such as inverse squared distance may provide greater accuracy without increasing the complexity of the method.

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NOTES AND REFERENCES

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2. Dr. Mark D. Shulman is Dean of academic and student affairs at Rutgers Cook College. Prior to his new appointment, he served as Professor and Chairman of The Department of Meteorology and Physical Oceanography, at Cook College and taught graduate and undergraduate courses. He has over 60 publications, mostly in the area of applied climatology. Dr. Shulman is a past President of the NWA and serves on the editorial staff of the Digest as Climatology Feature Editor.

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CORRIGENDUM

The following figure, from the article, ''Interpolation of Gridded Climatic Data for Use in Climatic Classification Schemes,' published in the August 1989 Digest, is reproduced to provide greater clarity.

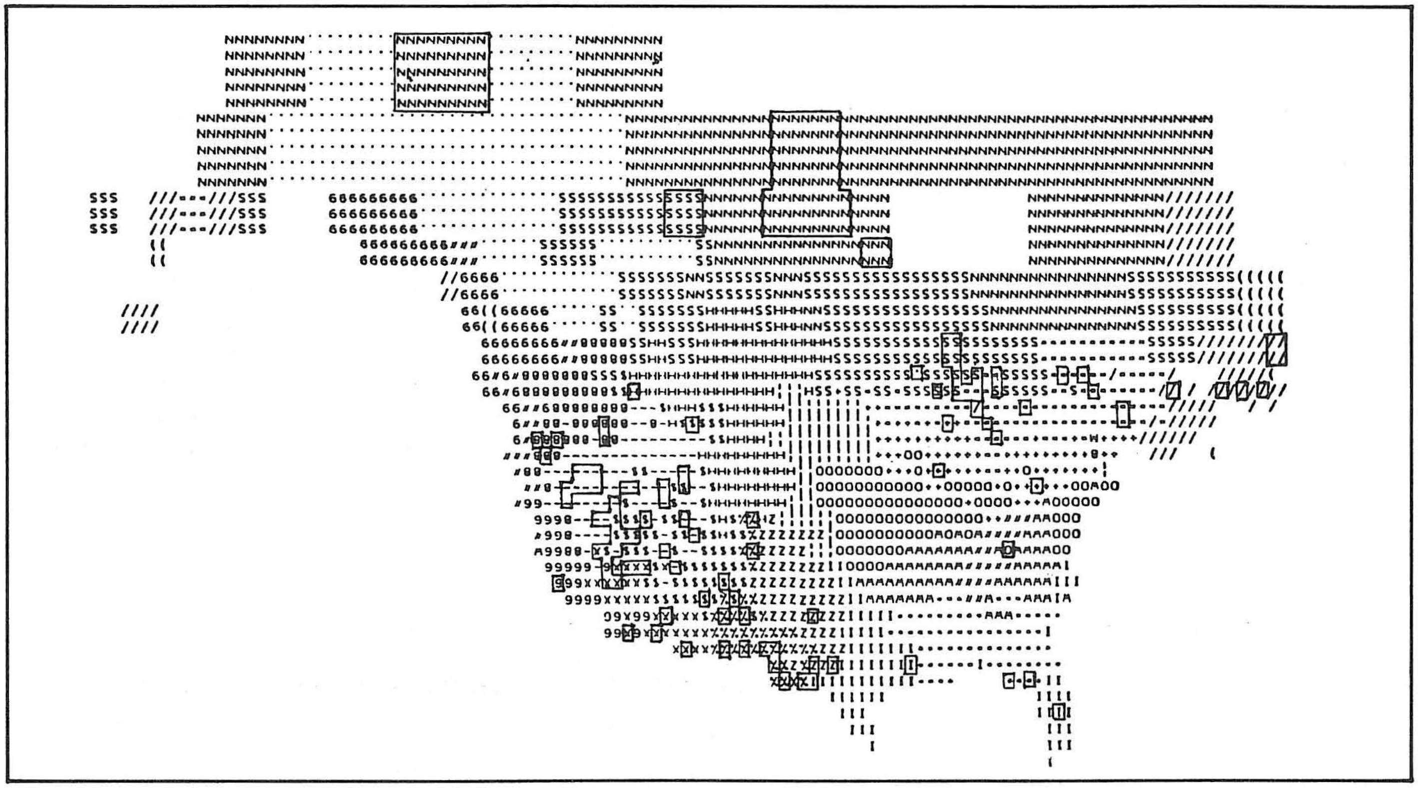

Fig. 4. Plant hardiness classification developed by DeGaetano and Shulman (14). Each symbol denotes a unique hardiness cluster. Grids with interpolated temperature and precipitation averages are outlined.

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