

CLIMATOLOGICALLY AIDED INTERPOLATION (CAI) OF TERRESTRIAL AIR TEMPERATURE

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ABSTRACT

A new and relatively straightforward approach to interpolating and spatially averaging air temperature from weather-station observations is introduced and evaluated using yearly station averages taken from the Jones *et al.* archive. All available terrestrial station records over the period from 1881 through to 1988 are examined. Called climatologically aided interpolation, or CAI, our procedure makes combined use of (i) a spatially high-resolution air-temperature climatology recently compiled by Legates and Willmott, as well as (ii) spatially interpolated yearly temperature deviations (evaluated at the stations) from the climatology. Spherically based inverse-distance-weighting and triangular-decomposition interpolation algorithms are used to interpolate yearly station temperatures and temperature deviations to the nodes of a regular, spherical lattice. Interpolation errors are estimated using a cross-validation methodology.

Interpolation errors associated with CAI estimates of annual-average air temperatures over the terrestrial surface are quite low. On average, CAI errors are of the order of 0.8°C, whereas interpolations made directly (and only) from the yearly station temperatures exhibit average errors between 1.3°C and 1.9°C. Although both the high-resolution climatology and the interpolated temperature-deviation fields explain non-trivial portions of the space–time variability in terrestrial air temperature, most of CAI's accuracy can be attributed to the spatial variability captured by the high-resolution (Legates and Willmott's) climatology. Our results suggest that raw air-temperature fields as well as temperature anomaly fields can be interpolated reliably.

KEY WORDS: interpolation; climatologically aided interpolation; air temperature

1. INTRODUCTION

Air temperature and its space–time variability continue to be examined extensively by climatologists for evidence of large-scale climatic change. A wide variety of approaches have been used, from climate-model simulations of temperature variability (e.g. Washington and Meehl, 1986) to the extraction of air temperature estimates from satellite observations (e.g. Spencer and Christy, 1990) and paleoclimatic records (e.g. Baron, 1982). Analyses based upon historical station-network records of shelter-height temperature, however, continue to be regarded as the most accurate or precise. Observational biases at the station locations have been investigated extensively (Mitchell, 1953; Karl *et al.*, 1989). Problems in estimating (i) the spatial variability within air temperature fields and (ii) spatial averages from station-network observations, however, have received insufficient attention, even though the errors and biases can be substantial (Willmott *et al.*, 1991; Robeson, 1993; Robeson and Willmott, 1993). Our focus within this paper then is on the spatial estimation problem; more specifically, we present and evaluate a relatively straightforward approach to the spatial interpolation and averaging of air temperature from station observations. As our estimation procedure makes use of a spatially high-resolution climatology, we call it climatologically aided interpolation, or CAI.

Although air-temperature anomalies—air-temperature deviations from station reference temperatures—are widely interpolated and averaged to characterize large-scale climatic change (Hansen and Lebedeff,

1987; Jones *et al.*, 1986a,b), our primary interest here is in actual air-temperature fields rather than anomaly fields. Actual air-temperature fields are more informative than anomaly fields in that they more fully represent the thermal state of the near-surface atmosphere. Consider, for instance, that atmospheric radiative emission and the phase changes of water depend on air temperature, not on temperature anomalies or other derived air-temperature statistics. Anomaly fields are popular because they are relatively free of the considerable topography-forced spatial variability that exists within actual air-temperature fields. Anomaly-field popularity also rests on two tacit assumptions: (i) actual air temperatures cannot be interpolated with acceptable levels of accuracy and (ii) spatial averages derived from the anomaly fields—obtained from different station networks and/or time slices of climate—are consistently related to their corresponding actual air-temperature fields and spatial averages. It is important to mention that the validity of this second assumption, to our knowledge, has not been rigorously demonstrated. Our analysis (below) additionally shows that the first assumption may be losing its validity.

Air-temperature fields are usually estimated at the nodes of a regular grid by spatially interpolating from a set of irregularly spaced station observations. Spatial averages, in turn, can be obtained by summing the grid-point temperature estimates, where each grid-point value is weighted by the area represented by the grid point. Interpolation to the grid can be performed using one of a wide variety of algorithms (Robeson, 1993; Robeson and Willmott, 1993), although here we rely primarily on a spherical version of Shepard's (1968) inverse-distance weighting method (Willmott *et al.*, 1985) because it is both relatively accurate (Bussi eres and Hogg, 1989; Weber and Englund, 1992) and cost effective. Renka's (1984) interpolation methods (based on a triangular decomposition of the data network on the sphere) also are examined. Our emphasis within this paper is on the errors associated with interpolating air-temperature fields by both traditional (simple) interpolation methods and by using a spatially high-resolution climatology to aid the interpolation.

2. SPATIALLY AND TEMPORALLY VARYING AIR-TEMPERATURE OBSERVATIONS

Jones *et al.* (1986a,b) published perhaps the most comprehensive study of global air-temperature changes over the last century and we make use of their data here. Although both the original station data and their estimated gridded form are available (Jones *et al.*, 1991), our interest is in interpolation from stations to the nodes of regular lattices and the associated errors; therefore, our analyses begin with the station air-temperature data. More precisely, we examine annual average air temperature at all available terrestrial stations for each year from 1881 through to 1988.

Numbers and distributions of the air-temperature stations contained within the Jones *et al.* (1991) archive are described in some detail in their documentation and elsewhere (e.g. Robeson, 1993). Such discussion, therefore, is not repeated here. A few comments about the Jones *et al.* (1991) station networks, however, illustrate several general problems associated with the spatial interpolation of terrestrial air temperature as well as the estimation of global climate change from irregularly spaced air-temperature data sets.

Within the Jones *et al.* (1991) data base, air-temperature records prior to 1881 were very few in number (<250) and most were obtained from stations in Europe and North America. Station networks for the late 1800s continue to overrepresent Europe and North America—relatively speaking. By 1901, terrestrial station networks are available for more than 500 stations. Available station records are greatest for the period 1951–1970 and nearly 1700 of these records are contained in the Jones *et al.* (1991) archive. Spatial distributions of stations generally become more even through time; although several undersampled areas persist, notably in Africa and South America. With this in mind, our analyses of terrestrial station networks begin with the 1881 network.

3. SPATIAL INTERPOLATION OF AIR TEMPERATURE BY TRADITIONAL METHODS

3.1. Interpolation methods

Estimating air temperatures at unsampled locations (e.g. grid points) from sampled locations (e.g. temperature stations) usually is accomplished by spatial interpolation (Bennett *et al.*, 1984). Although a number of

approaches are available (cf. Shumaker, 1976; Gustavsson, 1981; Franke, 1982; Lam, 1983; Thiébaux and Pedder, 1987), an example from each of two commonly used classes of interpolation methods are considered here. Mentioned above, inverse-distance weighting methods are represented by Willmott *et al.*'s (1985) spherical implementation of Shepard's (1968) procedure, whereas triangular decomposition is illustrated with Renka's (1984) C^0 algorithm and, to a lesser extent, his C^1 procedure. Interpolation errors associated with estimating terrestrial air-temperature fields are evaluated for each of these methods. A third class of interpolators, functional minimization, is not examined because of the massive number of computational cycles required when the number of stations is large (Robeson, 1993).

Interpolation by inverse-distance weighting remains popular because of its simplicity and relative accuracy (Bussi eres and Hogg, 1989; Weber and Englund, 1992; Robeson and Willmott, 1993). An air temperature at an unsampled location of interest (node i) can be estimated—by inverse-distance weighting—from nearby sampled locations (stations) according to

$$\hat{T}_i = \sum_{j=1}^{n_i} w_{ij} T_j / \sum_{j=1}^{n_i} w_{ij} \quad (1)$$

where each weight (w_{ij}) is an inverse function of the distance from a sampled location (j) to an unsampled location (i), T_j is an air temperature at nearby station j , and n_i is the number of nearby stations that influence the estimate at location i . Although the Willmott *et al.* (1985) algorithm (following Shepard, 1968) is based on powers of inverse distance—and therefore qualifies as an inverse-distance weighting scheme—it also contains two useful extensions. Outlined by Shepard (1968), biases arising from autocorrelation among spatially clustered nearby stations are reduced through the application of a cosine weighting function. Provision also is made for extrapolating beyond the range of the nearby stations when spatial gradients warrant it. Implementation of these extensions can be made by adjusting the weighting scheme in equation (1). Inverse-distance-based interpolation methods that do not possess some form of these two extensions are at a relative disadvantage, as discussed by Willmott and Legates (1991).

Spatial interpolation by triangular decomposition is similar to distance weighting in that nearby stations generally receive more weight than distant stations. The station network, however, is first decomposed into triangular elements (usually by a Delaunay triangulation). When interpolating over large areas of the Earth, it is important to perform the triangulation and other distance and angular calculations on the surface of a sphere, as Renka (1984) has done. After the station locations have been triangulated, a surface can be fitted over each triangular element. Any order surface can be used; but, care must be taken to ensure that each triangular patch fits with neighbouring patches both seamlessly and smoothly. Such triangulation and subsequent surface fitting form the basis of several widely used spatial interpolation routines. Akima's (1978) algorithm, for instance, is both well known and available within the IMSL and NCAR Graphics subroutine libraries. Like most interpolation algorithms, Akima's method was developed to interpolate data that are georeferenced in a plane. It, or other planar-based methods, should not, therefore, be used to interpolate spherically geocoded observations without modifications to incorporate the Earth's spherical geometry.

Unlike most procedures, Renka's (1984) algorithm permits both spherical triangulation and interpolation. It also includes both a C^0 (continuous but not differentiable) and C^1 (continuous and once differentiable) interpolants. Renka's C^0 method fits a planar surface over each spherical triangle, whereas the C^1 method applies a Hermitian cubic surface (other constraints restrict the surface to be differentiable only once). Spatial gradient estimation is required for the C^1 method and can be accomplished either locally or globally (Renka, 1984).

3.2. Interpolation errors

When interpolating any climatological field from irregularly spaced station data, it is useful to evaluate both the interpolation procedure and the adequacy of the station network. Cross-validation (Efron and Gong, 1983) provides a way to do both and it is used here. Our implementation of cross-validation is basic. The first step is to remove one observed data point (station air temperature) at a time from the station

network. One by one (with replacement), each removed station air temperature then is estimated by interpolation from surrounding station air temperatures. This two-step procedure is repeated for all stations, which yields an observed and estimated temperature at each station location. Differences between the corresponding observed and interpolated station temperatures (i.e. the interpolation errors) reflect both the fidelity of the interpolant and the adequacy of the station network (Robeson, 1993). Although these two sources of error can be difficult to separate, comparisons among interpolation methods (e.g. Robeson, 1993) can identify the relative accuracy of competing methods.

Both Willmott *et al.*'s (1985) and Renka's (1984) C^0 methods are evaluated using the above-described cross-validation analysis. Interpolation errors for the air-temperature data drawn from Jones *et al.* (1991) are large—mean absolute errors (MAEs) range from *ca.* 1.3°C for the densest networks to *ca.* 1.9°C for the sparsest ones. Time series of MAE (Figure 1) also exhibit a strong inverse relationship between interpolation error and number of stations. Cross-validation errors additionally suggest that the Willmott *et al.* procedure performs better than Renka's C^0 method for these air temperature data. Differences between Willmott *et al.*'s and Renka's C^0 methods, however, appear not to be statistically meaningful for a number of years, as estimated by boot-strapped 95 per cent confidence intervals (not shown). The cross-validation also suggests that a few hundred stations (i.e. station networks from the 1880s) or even 1500 stations (i.e. station networks from the 1950s and 1960s) do not represent terrestrial air-temperature variability adequately (interpolation MAEs are $>1.3^\circ\text{C}$).

The greater accuracy exhibited by the Willmott *et al.* algorithm, relative to Renka's C^0 method, most likely results from a combination of differences between these two methods, although the inclusion of spatial derivatives within Willmott *et al.* and not within Renka is worth noting. Renka's C^1 method also was tested because it estimates spatial gradients and fits a higher order surface, unlike the C^0 method. Highly irregular station distributions appear to pose problems for both the local and global gradient-estimation calculations within the C^1 method, however. The C^1 cross-validation errors for some networks consequently have MAEs exceeding 3.0°C .

As illustrated above, traditional or simple interpolation algorithms often are inadequate when the field of interest is spatially variable and the observational network is sparse. Traditional, simple or univariate interpolation refers here to interpolation methods that rely solely on observations of the variable being interpolated at a set of sampled locations; that is, the only independent variables are T_j (in our case), x_j , and y_j , where x_j represents longitude and y_j latitude. Researchers from several disciplines, however, have attempted to use additional independent variables to reduce the between-station uncertainty. Climatologically aided interpolation (CAI) is another such multivariate method, and it is presented and evaluated below.

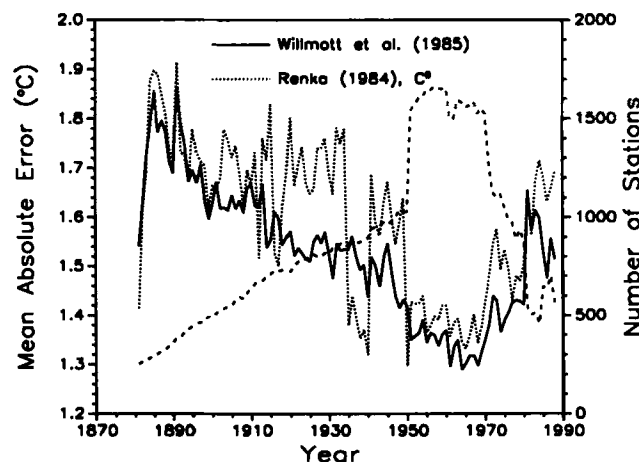


Figure 1. Time series of spatially integrated mean absolute interpolation error (MAE) from cross-validation analyses using air temperatures. Willmott *et al.*'s (1985) algorithm (solid line) and Renka's (1984) C^0 method (dotted line) were used to interpolate air temperature to each station from surrounding stations. The number of air-temperature stations through time (dashed line) also is shown.

4. CLIMATOLOGICALLY AIDED INTERPOLATION (CAI) OF AIR TEMPERATURE

Climatologically aided interpolation makes use of a climatological (long-term average) air-temperature field to help interpolate an annual air-temperature field of interest. Intra-annual climatic variables (e.g. monthly air temperature) also could be interpolated in a similar fashion. As the climatological field represents additional information, CAI can be thought of as a type of multivariate method. For multivariate interpolation to improve on univariate methods, at least one additional variable must exist that is (i) highly collinear in space with the variable of interest and (ii) observed at a meaningfully higher spatial resolution or where the variable of interest is unsampled. The CAI method exploits the spatial collinearity between recent high-resolution station-based climatologies of air temperature (e.g. Legates and Willmott, 1990) and annual temperature observations associated with lower resolution station networks (e.g. Jones *et al.*, 1991).

Our implementation of CAI grows out of the interdisciplinary interpolation literature as well as several years of experiments at the University of Delaware. A number of intriguing approaches have taken form within the atmospheric sciences under the somewhat nebulous rubric 'objective analysis', and other advances have appeared under a wide variety of banners. Multivariate objective methods, for instance, are used to adjust numerical weather-model simulations toward consistency with current weather observations (Daley, 1991). Climatological (time-averaged) information also has been used to refine objective interpolations of upper-air fields from soundings (Thiébaux and Pedder, 1987). Ishida and Kawashima (1993) recently articulated the advantages of incorporating a high-resolution digital elevation model (DEM) into an air-temperature interpolation scheme. Anomaly-based interpolation (e.g. Jones *et al.*, 1986a,b) also makes use of additional information, albeit—like CAI—information about the variable of interest but from a different time period.

Our implementation of CAI again makes use of Willmott *et al.*'s interpolation algorithm as described below (section 4.2). Before considering CAI in some detail, however, we summarize the pertinent characteristics of the Legates and Willmott (1990) high-resolution air-temperature climatology.

4.1. A spatially high-resolution climatology of terrestrial air temperature

Among the more spatially extensive air-temperature climatologies that are available is the compilation of Legates and Willmott (1990). It contains monthly and annual mean air temperatures for nearly 18 000 terrestrial stations (Figure 2(a)); that is, several-fold more stations than exist within the most complete archives of station time-series of air temperature (e.g. Vose *et al.*, 1992; Jones *et al.*, 1986a,b). Unlike

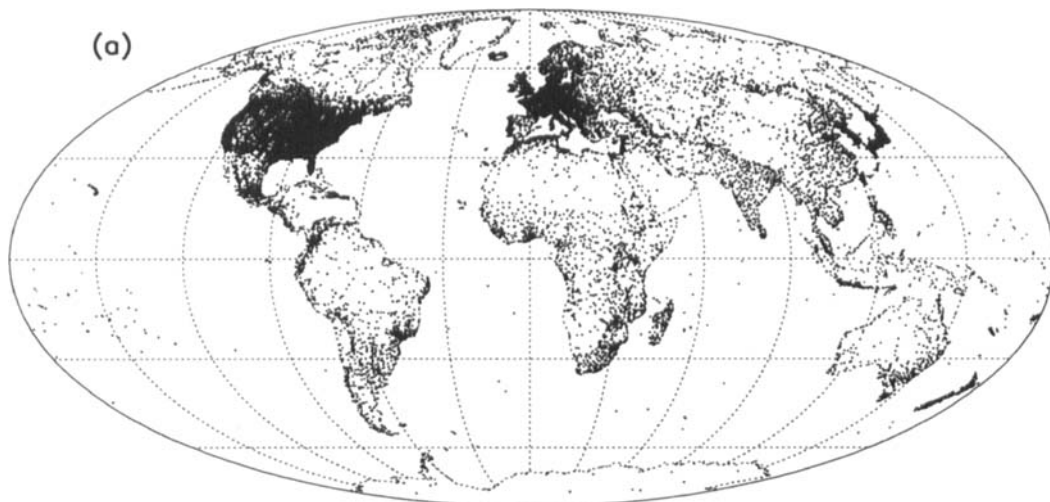


Figure 2(a). Spatial distribution of the 17986 air-temperature stations of Legates and Willmott (1990).

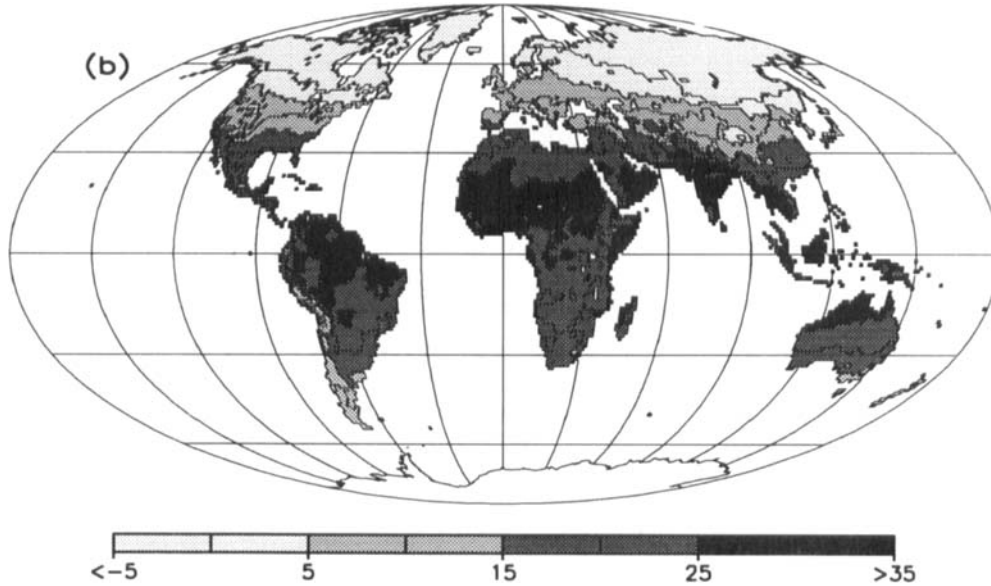


Figure 2(b). Spatial distribution of annual mean temperature ($^{\circ}\text{C}$) from the climatology of Legates and Willmott (1990).

air-temperature fields interpolated from just a few hundred stations, the Legates and Willmott climatology is able to resolve much of the small-scale spatial air-temperature variability (Figure 2(b)). Features such as the Ethiopian highlands and the sharp boundary between the Atacama Desert and the Andes are clearly delineated. Its main drawbacks are: (i) it is comprised of climatological averages and therefore cannot resolve interannual variability and (ii) it contains selected station averages from differing, albeit usually overlapping, time periods—to ensure maximum spatial coverage. For many spatial applications, its high spatial resolution outweighs the deleterious effects of variable averaging periods. Preliminary work by the authors using precipitation data suggests that interpolation errors (when using traditional interpolation methods) are greater when station records from different averaging periods are left out rather than included.

4.2. Interpolation of air temperature using CAI

Long-term station means from a high-resolution climatology (Legates and Willmott's climatology in this instance) first are subtracted from the annual-average station temperatures at all stations available for a year of interest (from the Jones *et al.* archive in this case). In this way, an annual temperature deviation (δT_j) is obtained for each station. When a climatological mean does not exist for a station, it can be interpolated from nearby climatological means. Station deviations from long-term station means (δT_j) then are interpolated to a spherical lattice. At each node of the grid, our CAI estimate (\hat{T}_i) is obtained by adding the interpolated deviation (δT_j) to Legates and Willmott's long-term average (\bar{T}_i), where each \bar{T}_i was previously interpolated from Legates and Willmott's 17 986 long-term station averages. When δT_j is interpolated by inverse-distance weighting, we can write

$$\hat{T}_i = \bar{T}_i + \frac{\sum_{j=1}^{n_i} w_{ij} \delta T_j}{\sum_{j=1}^{n_i} w_{ij}} \quad (2)$$

In this way, our implementation of CAI includes both the spatially high-resolution information within the climatology as well as observations for a given year or other time-period of interest.

Although inconsistencies arising from station observational biases (e.g. time-of-observation differences among countries, differential urban heating, and station records that span variable time periods) exist within Legates and Willmott's climatology, CAI indirectly damps their deleterious influences on the interpolated yearly temperature fields in the following way. Our δT_j fields represent not only the climatologically forced

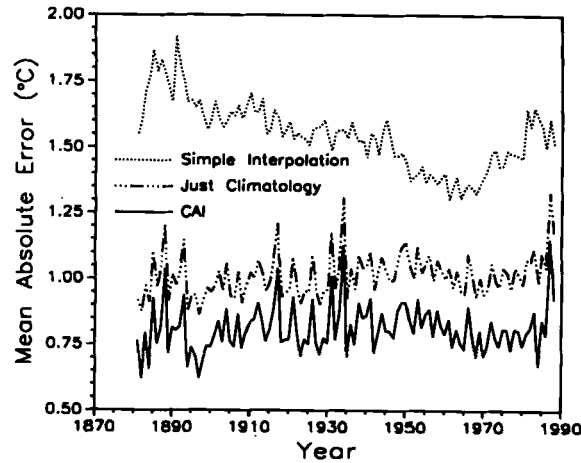


Figure 3. Time series of spatially integrated mean absolute interpolation error (MAE) from cross-validation analyses of (i) Willmott *et al.*'s (1985) interpolations from Jones *et al.*'s yearly station data (dotted line), (ii) climatologically aided interpolation (CAI) again interpolating with Willmott *et al.* (solid line), and (iii) climatology alone (mixed dashed and dotted line).

differences between the interpolated Legates and Willmott (\bar{T}_j) and Jones *et al.* (T_j) temperatures at station j , but they also contain information about station biases that influence differences between \bar{T}_j and T_j . When the δT_i field is interpolated from the δT_j field, it (the δT_i field) then contains interpolated bias-correction information; in turn, when the δT_i field is added to the estimated \bar{T}_i field, the grid-point estimates approximate the Jones *et al.* station values in quality, albeit at a much higher spatial resolution. It is this aspect of our somewhat unusual anomaly fields that allows CAI to effectively make use of the inhomogeneous—but spatially high-resolution—station records that reside in Legates and Willmott's climatology.

4.3. Interpolation errors for CAI

Cross-validation was performed (as in section 3.2) for CAI using Willmott *et al.* (1985) to interpolate both the \bar{T}_j and the δT_j . Substantial improvements over the simple interpolation results (using only yearly air temperatures) are apparent (Figure 3). Interpolation errors are reduced by over 50 per cent, and approach interpolation errors associated with more standard anomaly data (Robeson, 1993). Scatter plots (Figure 4)

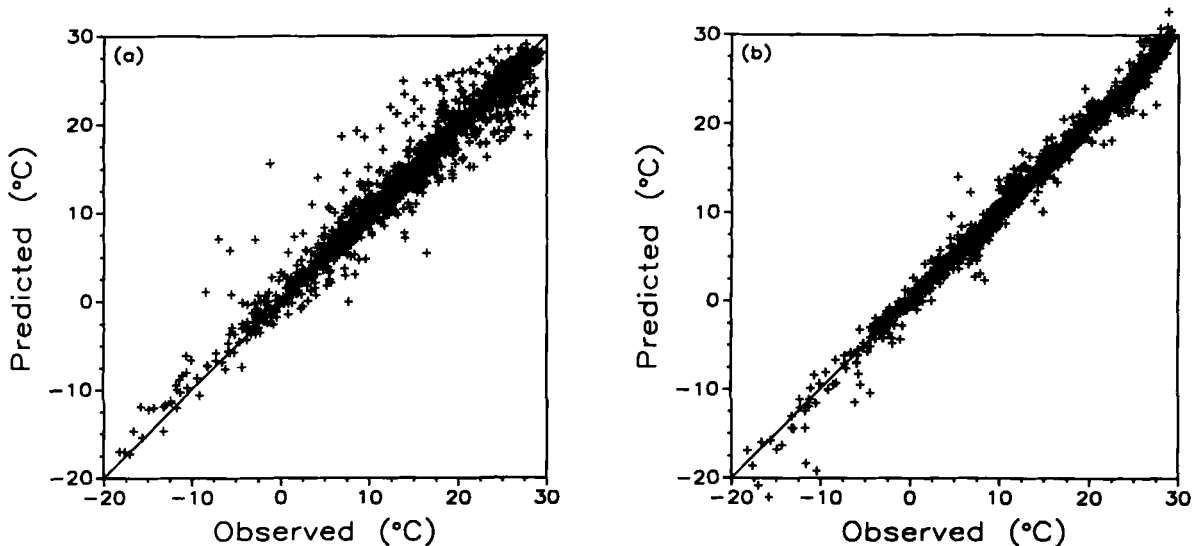


Figure 4. Scatter plots of observed air temperature versus cross-validation estimates for 1962 using (a) Willmott *et al.*'s algorithm with the yearly station data only and (b) climatologically aided interpolation (CAI).

provide further convincing evidence of the superior performance of CAI even for densest station networks (ca. the 1950s and 1960s).

Unlike the errors associated with simple interpolation, CAI cross-validation errors are not highly correlated with the number of stations. Explanation lies in the somewhat counter-intuitive fact that the spatial variability within the climatology accounts for most of the temporal (yearly) between-station air-temperature variability. For typical yearly station networks, in other words, more between-station variability is spatial than temporal. The CAI method works especially well for air temperature because the high-resolution climatology indirectly accounts for topography as well as the spatial variability in the average characteristics of climate. Our results also strongly suggest that air temperatures—not just air-temperature anomalies—can be interpolated reliably, even from sparse station networks.

Although CAI reduces cross-validation errors for yearly air-temperature data, it is useful to examine the separate roles that the interpolated deviation field and climatology play. When climatology alone is used as the cross-validation estimate at each station (i.e. $\hat{T}_j = \bar{T}_j$, where \bar{T}_j is interpolated), it is clear that its relative contribution is substantial (Figure 3). Interpolation errors for just the climatology, in fact, are of the order of a half degree lower than the average error incurred in simple interpolation from the yearly air-temperature station networks. Once again, the primary reasons why Legates and Willmott's climatology explains such a large portion of the spatial variability in yearly temperature are that (i) its average station density is roughly tenfold greater than the station densities of most climatologies containing only homogeneous (in time) station records, and (ii) much of the space-time variability in yearly mean temperature is spatial and occurs at scales below the station-network resolutions of most temporally homogeneous climatologies. A non-trivial portion of the spatial variance (ca. 0.2°C) also is explained by the interpolated δT field. It is intriguing that (i) the high-resolution climatology is the most important component of CAI and (ii) CAI is dramatically superior to simple interpolation for all the station networks evaluated (Figure 3).

5. SUMMARY AND CONCLUSIONS

Several interpolation methods were applied to the spatial estimation of yearly air-temperature averages for stations drawn from the Jones *et al.* (1991) data set. Traditional or simple interpolation methods were represented by the inverse-distance weighting algorithm of Willmott *et al.* (1985) and Renka's (1984) triangular decomposition methods. A new approach termed climatologically aided interpolation (CAI) also was evaluated and compared with the traditional methods. All interpolation procedures and all yearly station networks within the Jones *et al.* (1991) archive were used to interpolate annual-average station temperatures. Cross-validation was used to estimate the interpolation errors.

Interpolation errors for the simple interpolation methods ranged from 1.3°C to 1.9°C, approximately. Errors associated with our implementation of CAI were considerably lower—of the order of 0.8°C. Most of the improvement exhibited by CAI (relative to simple interpolation) can be attributed to the spatially high-resolution station network contained in the Legates and Willmott climatology. When it alone was used to estimate the yearly station temperatures, interpolation errors were of the order of 1°C. The interpolated deviation field then accounted for about 0.2°C of the spatial variability. Although both the climatology and the interpolated air-temperature deviation fields explained significant portions of the yearly spatial variance in air temperature, the spatial variability captured by the high-resolution climatology appears to be considerably more important.

Our sense is that the use of additional independent variables in spatial interpolation (i.e. multivariate interpolation) will increase dramatically as the number and quality of available high-spatial-resolution data bases increases. Satellite and high-resolution archives of other important climatic variables, in particular, should measurably improve our ability to interpolate, map, and evaluate climate and climatic change. Spatially high-resolution estimates of average lapse rates—made from high-resolution digital elevation models (DEMs)—also should significantly improve the accuracy and resolution of our interpolated air-temperature fields. The CAI of air temperature provides one example of the substantial increases in accuracy that are possible. Such methods also should improve spatial interpolations of climate variables at smaller spatial scales.

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