NOTES AND CORRESPONDENCE

Drought Index Mapping at Different Spatial Units

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ABSTRACT

This paper investigates the influence of spatial interpolation and aggregation of data to depict drought at different spatial units relevant to and often required for drought management. Four different methods for drought index mapping were explored, and comparisons were made between two spatial operation methods (simple unweighted average versus spatial interpolation plus aggregation) and two calculation procedures (whether spatial operations are performed before or after the calculations of drought index values). Deterministic interpolation methods including Thiessen polygons, inverse distance weighted, and thin-plate splines as well as a stochastic and geostatistical interpolation method of ordinary kriging were compared for the two methods that use interpolation. The inverse distance weighted method was chosen based on the cross-validation error. After obtaining drought index values for different spatial units using each method in turn, differences in the empirical binned frequency distributions were tested between the methods and spatial units. The two methods using interpolation and aggregation introduced fewer errors in cross validation than the two simple unweighted average methods. Whereas the method performing spatial interpolation and aggregation before calculating drought index values generally provided consistent drought information between various spatial units, the method performing spatial interpolation and aggregation after calculating drought index values reduced errors related to the calculations of precipitation data.

1. Introduction

The social and economic costs of drought require decision makers to improve planning, mitigation, and adaptation strategies to deal with this hazard. Monitoring constitutes an essential part of drought preparedness, and proactive measures to reduce the consequences of drought require information at increasingly finer spatial resolutions. Because the spatial density of weather stations limits the depiction of drought at high resolution, spatial analytical tools must be used to approximate spatial distributions of drought. This paper investigates the influence of spatial interpolation and aggregation of data to depict drought at various spatial units.

Drought monitoring often uses one or more indices, such as the Palmer drought index (PDI; Palmer 1965) or the standardized precipitation index (SPI; McKee et al. 1993), to measure drought intensity. These indices can be calculated at individual weather stations or for a specified area; for example, the PDI is commonly calculated for climate divisions. The National Climatic Data Center (NCDC) produces climate divisional PDI and maintains a century-long archive of the values that has proven useful for a wide variety of analyses and applications (e.g., Strommen et al. 1966; Cook et al. 1988; Carbone and Dow 2005).

Although representing drought at the climate divisional level provides sufficient information for detecting the large-scale drought patterns of the 1930s, 1950s, and 1980s (Guttman and Quayle 1996), it lacks the detail that is increasingly demanded for drought management decisions. Some of this demand stems from the simple realization that indices for large regions obscure

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differences within the regions. Some of it reflects the societal reality that drought can be managed by decision makers whose jurisdictions include counties, watersheds, or other units. Because it is possible to present drought intensity at different spatial units, the assessment of the methods used to do this (i.e., interpolation and spatial aggregation) deserve attention.

We compare four methods for drought index mapping at different spatial units. After obtaining drought index values for various spatial units using each method in turn, any differences in the empirical binned frequency distributions between spatial units are tested to find out which methods provide consistent drought information for various spatial units. All tests are performed for North and South Carolina, where the demand for refined regional drought monitoring has increased since the 1998–2002 drought. Strengths and weaknesses of each method are discussed in the conclusions section.

2. Study area and data

The study area is North and South Carolina (Fig. 1). The elevation varies only moderately except for the Blue Ridge region. Although the study area is characterized by a subtropical humid climate with no marked dry season, there have been severe droughts almost every decade since the first records from the early nineteenth century (Zemburszki et al. 1991; Stringfield et al. 1991). The 1998–2002 drought in North and South Carolina devastated agriculture, threatened municipal water systems and industry, and caused regional economic stress (Weaver 2005; Carbone et al. 2008). The drought exposed the need for monitoring at greater temporal and spatial resolution. Rhee and Carbone (2007) addressed the temporal issue by proposing a method for calculating weekly PDI values that approximates monthly PDI within the conventionally used value range, preserves memory on drought conditions, and provides a tool for progressive drought monitoring that enables users to identify the onset of drought earlier and more clearly. Carbone et al. (2008) demonstrated a visualization tool for displaying drought information at different spatial units. This paper evaluates the interpolation and aggregation methods used to produce these visualization tools for decision support. “Spatial unit” in this paper refers to the division of a specific area (e.g., counties). Each entity, such as Richland County of South Carolina, is defined as a “spatial feature.”

In addition to climate divisions, we examine two specific spatial units: counties and the United States Geological Survey (USGS)’s various hydrologic unit codes (HUCs). While drought information at the county level would help those involved in disaster declaration, the USGS HUCs define watershed basins at different levels (Seaber et al. 1987). They have a hierarchical structure with coincident boundaries and include regions (two-digit HUCs), subregions (four-digit HUCs), basins (six-digit HUCs), and subbasins (eight-digit HUCs). We include these units because watersheds play a pivotal role in drought management practices and water resources planning. There are 146 counties, 15 climate divisions, three regions, nine subregions, 14 basins, and 92 subbasins in North and South Carolina (Fig. 2).

Daily maximum and minimum temperatures and 24-h total precipitation data for 238 Cooperative Observer Program (COOP) stations were obtained from the Applied Climate Information System (ACIS) for the period 1975–2004. Among the stations, 78 stations outside the Carolinas were included to reduce the edge effect of spatial interpolation (Fig. 1). Stations with historical data from 1950 with less than 20% of missing data were selected. The percentages of missing data for recent years for all stations are very low, and all daily missing data were replaced with the 30-yr normal values from 1971–2000. Historical daily normal values are more appropriate than spatially interpolated values for filling in missing data in this study because spatial operation methods of simple unweighted average and spatial interpolation are compared later, and the use of spatial interpolation for data preprocessing might affect the results. Monthly drought index values for the PDI (Palmer 1965; in which values $\leq -4.00 = \text{extreme drought, from } -3.00 \text{ to } -3.99 = \text{severe drought, from } -2.00 \text{ to } -2.99 = \text{moderate drought, from } -1.00 \text{ to } -1.99 = \text{mild drought, from } -0.50 \text{ to } -0.99 = \text{incipient drought}$).
drought, from −0.49 to 0.49 = near normal, from 0.50 to 0.99 = incipient wet spell, from 1.00 to 1.99 = slightly wet, from 2.00 to 2.99 = moderately wet, from 3.00 to 3.99 = very wet, and ≥4.00 = extremely wet) including the Palmer drought severity index (PDSI), Palmer hydrological drought index (PHDI), Palmer’s soil moisture anomaly (Z) index, and 1-, 3-, 6-, 9-, 12-, and 24-month SPI (McKee et al. 1993; in which values ≤−2.00 = extreme drought, from −1.50 to −1.99 = severe drought, from −1.00 to −1.49 = moderate drought, from −0.99 to 0.99 = near normal, from 1.00 to 1.49 = moderately wet, from 1.50 to 1.99 = very wet, and ≥2.00 = extremely wet) were calculated from monthly temperature and precipitation values.

3. Methods

a. Comparison of interpolation techniques

Four methods for drought index mapping at different spatial units are outlined in the next section. Two methods include spatial interpolation procedures, another method requires the interpolation of temporally aggregated precipitation data as well as monthly temperature, and the other method involves the interpolation of drought index values. The most appropriate interpolation technique for each variable was selected prior to the comparison of the four methods using cross validation.

Deterministic interpolation techniques including Thiessen polygons (nearest neighbor), inverse distance weighted (IDW), and thin-plate splines were evaluated as well as ordinary kriging, a stochastic and geostatistical interpolation technique. The Thiessen polygon method assigns values of the nearest stations to unsampled locations (Thiessen 1911). The IDW method estimates the values of unsampled locations by weighting observations based on their distance from unsampled locations (Shepard 1968). The significance of the distance in IDW is determined by the power parameter. Thin-plate splines and ordinary kriging were described by Wahba (1990) and Cressie (1993), respectively, in detail. Thiessen polygons and IDW were applied using Python programs, whereas the thin-plate splines and ordinary kriging were performed using Environmental Systems Research Institute’s (ESRI) ArcMap 9.1 geostatistical analysis software. Spherical models were used to fit the empirical semivariograms for ordinary kriging with the default setting of the software.

Universal kriging and ordinary cokriging were also tested. For both the meteorological data and drought index values, the interpolation results using ordinary and universal kriging were very similar. The correlations between interpolated and environmental variables (latitude, longitude, elevation, and distance to sea) were obtained using simple linear regression analy-
ses to find the most appropriate secondary variable for ordinary cokriging. However, the correlation coefficient values were low and were not statistically significant in almost all cases. Thus, universal kriging and ordinary cokriging were not included for the comparisons of cross-validation errors.

Because of the low density of available weather stations, the search radius criterion was used instead of the number of stations criterion to avoid using distant stations. The same search radius criterion was applied to all of the interpolation techniques. For each grid cell, all of the weather stations within a circle, centered on the centroid of the grid cell and with a radius equal to the search radius, were used for interpolation. The initial radius was determined as 50 km, which is the radius of an imaginary circle with an area equal to the average of the mean area of the counties and climate divisions in North and South Carolina. Search radii of 50, 100, and 150 km were used to compare interpolation techniques, and a range of search radii from 50 to 200 km was tested for the IDW only. Search radii larger than 200 km were not considered because the weather stations in Georgia, Tennessee, and Virginia cannot eliminate the edge effect for boundary grid cells with these radii. Using weather stations that are too distant may cause poor estimation and misleading results.

The comparison of interpolation techniques was carried out for each variable interpolated, based on January and July values for the period from 1995 to 2004. This period was selected because it contains equal numbers of both wet and dry years. The “leave one out” cross-validation technique (Efron and Gong 1983) was used for validation. This method uses each observation as a validation datum and compares it to the estimated value for the location. Only the 160 weather stations within the Carolinas were used for cross validation, and the root-mean-square error (RMSE) and mean absolute error (MAE) values of the estimation errors were used as criteria for comparing interpolation techniques.

Skewed distributions cause errors during interpolation. Although SPI is standardized and PDI and monthly temperature are assumed to have Gaussian distributions, temporally aggregated precipitation data tend to be skewed. The removal of the skewness by the transformation of the distributions, followed by the back transformation after interpolation, was considered. Square root transformed (Hutchinson 1998), cube root—transformed (Stidd 1973), logarithmic transformed (Nalder and Wein 1998), and untransformed (raw) temporally aggregated precipitation data (for 1, 3, 6, 9, 12, and 24 months) were tested for normality using the Kolmogorov–Smirnov (K–S) test using SAS 9.1 software. The overall cross-validation RMSE and MAE values for each transformation were also compared. The back transformation introduces additional errors because interpolation techniques, such as kriging, find the best linear unbiased estimate (BLUE) using the transformed distribution (Prudhomme and Reed 1999).

b. Interpolation and spatial aggregation

The monthly temperature and precipitation data for each climate division are calculated by NCDC as simple unweighted averages of monthly temperature and precipitation data from all representative stations within the climate division (Guttman and Quayle 1996). Then, the monthly divisional drought index values are calculated based on the temperature and precipitation data. NCDC’s existing method is easy to use and understand, but it reveals some weaknesses when used for small spatial features. Because the method only uses weather stations within each spatial feature, relatively small spatial features cannot have values when the stations are not densely distributed. Another weakness appears when the weather stations are not evenly distributed. If stations are located only in some parts of the spatial feature, it is inappropriate to consider the simply averaged value to represent the actual condition of the feature. The calculation procedure may cause additional errors; simple averaging of monthly precipitation data from weather stations is inappropriate because the distribution tends to be skewed.

Although impossible, the actual drought condition of a region would ideally reflect every part of it. Here, we examine the effects of methods used to characterize drought across space in the absence of a high-resolution monitoring network. We consider two spatial operation methods (simple unweighted average versus spatial interpolation plus aggregation) and two calculation procedures (whether spatial operations are performed before or after the calculations of drought index values). These four drought index mapping methods (SimpleA, SimpleB, InterpolA, and InterpolB) were examined at different spatial units (Table 1). We chose an interpolation grid of 4 km × 4 km based on the trade-off between the advantages of high spatial resolution and computational load.

The difference between the simple unweighted average method and the interpolation plus spatial aggregation method was tested using a two-way chi-square test, using the empirical binned frequency distributions between SimpleA and InterpolA as well as between SimpleB and InterpolB for each spatial unit. The difference between the orders of procedures was also tested for each spatial unit to determine whether it matters if the spatial operations are performed before or
after calculating the drought index values. Because the independence assumption of the two-way chi-square test is not met, a resampling method (Efron and Gong 1983) was used to assess significance, wherein 1000 samples of size 3000 were selected from the population of drought index values during 1975–2004. Each observation of each sample was randomly selected with replacement. The empirical binned frequency distributions were obtained and the two-way chi-square test was performed for each sample. Finally, the percentage of the samples (out of 1000) showing any difference between the methods was calculated for each spatial unit.

c. Comparison of distributions at different spatial units

The differences of the empirical binned distributions for each of the four methods were compared between different spatial units based on the drought index data during 1975–2004. They were also tested using a two-way chi-square test using the empirical binned frequency distributions between counties and climate divisions as well as between different USGS hydrologic units. The resampling method described above was used. The comparisons for differences showed which methods between the different spatial units provide consistent drought information.

4. Results and discussion

a. Comparison of interpolation techniques

When the normality of the temporally aggregated precipitation data was tested using a K–S test with January and July values during 1995–2004 for several methods of transformation, the square root transformation produced distributions close to a Gaussian distribution for 1-month precipitation and the logarithmic transformation did the same for 3-, 6-, 9-, 12-, and 24-month precipitation data. Although, in some cases, the normality of the distributions was rejected even after the transformation, the effect of the transformation methods could be compared using the K–S test statistics.

Overall cross-validation RMSE and MAE values were obtained using the months of January and July from 1995–2004 for each interpolation method and for each interpolated variable with the search radius of 50 km (Figs. 3a,c for three-month SPI). Raw and logarithmic transformed precipitation values aggregated for 3, 6, 9, 12, and 24 months were assumed to behave like the monthly precipitation. The Thiessen polygons and the thin-plate splines methods showed relatively large RMSE and MAE values for all interpolated variables (Figs. 3a,c for three-month SPI).

Existing studies state that geostatistical interpolation methods perform better with sparsely distributed weather stations, whereas deterministic interpolation methods perform better when stations are densely located (Goovaerts 2000; Dirks et al. 1998). The density of weather stations in the study area is much lower than the criterion for a fine network introduced by Dirks et al. (1998), which is about 13 stations spaced over 35 km² (500 times denser than in this study area). Despite the sparse distribution of weather stations, there was almost no difference between the geostatistical method ordinary kriging and the deterministic method (IDW) for all the interpolated variables, primarily because of the moderate topographic variability in the study area. However, the possibility that the lack of difference may have been a result of the confinement of the 50-km search radius could not be ignored. Thus, the cross-validation RMSE and MAE values for a 100-km search radius were also calculated (Figs. 3a,c for three-month SPI).

The results for the Thiessen polygons method did not change because the nearest neighbor weather station remained the same regardless of the search radius. The cross-validation RMSE and MAE values decreased for other methods because more information from distant stations was used. The values for the thin-plate splines were larger than the values for the ordinary kriging and the IDW, and the ordinary kriging and the IDW showed comparable values similar to the results of the 50-km search radius for all interpolated variables (Figs. 3a,c for three-month SPI). The cross-validation RMSE and MAE values with greater search radii (150 and
200 km) were also examined, and the errors were larger than the values with a 100-km search radius. This suggests that the optimum search radius is somewhere between 50 and 150 km. It may be a result of the effect of moderate topographic variability in the Carolinas, which contributes to the climatic characteristics of the area.

Because the ordinary kriging and IDW showed comparable results and the IDW provides much simpler calculations, the IDW was selected in this study. The optimum power parameter and search radius for interpolated variables were sought based on the overall cross-validation RMSE and MAE values using a Python program. The power parameter of 1.3 with the search radius of 90 km was selected for all drought indices (average number of stations = 9.5; density = 6.2 stations per 10^4 km^2), and the power parameter of 1.5 with the search radius of 70 km was selected for all precipitation data, regardless of the temporal aggregation or the transformation (average number of stations = 16.0; density = 6.3 stations per 10^4 km^2). The search radius of 120 km with the power parameter of 2.4 was the most appropriate for the monthly temperature (average number of stations = 27.5; density = 6.1 stations per 10^4 km^2), although the IDW interpolation of monthly temperature performed consistently well for a range of search radii (70–120 km) and power parameters (1.5–2.4). The selected power parameter values (>1.0) implies that the geographical distance in the study area plays a more important role than in the local averaging, which is an equivalent to the IDW with a power parameter of 1.0.

For comparison, the cross-validation RMSE and MAE values of the simple unweighted average method were obtained by assigning the averaged value from all of the available weather stations to all of the grid cells within each spatial feature for each spatial unit (Figs. 3b,d for three-month SPI). Large spatial units of regions and subregions have large RMSE and MAE values for all the interpolated variables because each grid...
cell was assigned values with information not only from close stations but also from distant stations (Figs. 3b,d for three-month SPI). Only counties and subbasins with weather stations could be considered because 6 counties in South Carolina, 24 counties in North Carolina, and nine subbasins contain no weather stations. The RMSE and MAE values of counties and subbasins are also large because of the small number and uneven distributions of weather stations. Climate divisions produced the lowest errors for all of the interpolated variables and for RMSE and MAE values among the spatial units compared (Figs. 3b,d for three-month SPI). It suggests that the spatial unit of climate divisions is appropriate if the simple unweighted average method is used. The RMSE and MAE values were larger, however, than the values from the IDW and ordinary kriging with 50- or 100-km search radii (Fig. 3 for three-month SPI).

b. Interpolation and spatial aggregation

The PDI (PDSI, PHDI, and Z index) and SPI (1, 3, 6, 9, 12, and 24 months) values for 1975–2004 were calculated using the four methods (Table 1) for spatial units of counties, climate divisions, regions, subregions, basins, and subbasins. Because SimpleA and SimpleB do not allow values for spatial features with no stations, only spatial features with valid data for all four methods were considered for comparisons for counties and subbasins.

Each of the 79 out of 149 counties and the 25 out of 92 subbasins contains only one weather station. Thus, the methods using simple unweighted average (SimpleA and SimpleB) make no difference for these spatial features (Figs. 4a and 5). The methods using interpolation and spatial aggregation (InterpolA and InterpolB) showed different results from SimpleA and SimpleB because they incorporate the information from nearby stations (Figs. 4a and 5). Whether to use information only from weather stations within the spatial feature or to include information from outside weather stations using interpolation is a critical decision, especially for small spatial units; the nearby weather stations provide important information for the areas near the boundaries. The time series 24-month SPI values during 1995–2004 for all four methods for the Black River watershed basin (subbasin 03030006; contains one weather station) are shown in Fig. 4a. The differences between methods for the number of stations included, whereas the differences caused by the calculation procedures are dominant when many stations are included.
ures are shown as mean absolute differences of 24-month SPI (Fig. 5). Although fluctuation occurred because the density of stations was not considered, general trends could be observed.

Many spatial features of small spatial units have more than one but only a few weather stations. For these spatial features, the differences caused by the inclusion of nearby stations (SimpleA versus InterpolA; SimpleB versus InterpolB) appeared throughout the entire period. The differences caused by the calculation procedures (SimpleA versus SimpleB; InterpolA versus InterpolB) were shown during wet conditions (Fig. 4b). The time series 24-month SPI values during 1995–2004 for all four methods for the Lumber River watershed basin (subbasin 03040203; contains two weather stations) are shown in Fig. 4b.

The differences caused by the calculation procedures were clearly shown for moderate spatial units of basins, climate divisions, and large spatial units of regions and subregions (Fig. 5). In general, SimpleB and InterpolB indicated wetter conditions for relatively wet periods and drier conditions for relatively dry periods compared to SimpleA and InterpolA (Fig. 4c). The time series 24-month SPI values during 1995–2004 for all four methods for the Pee Dee River watershed basin (subregion 0304; contains 37 weather stations) are presented in Fig. 4c. These differences arise primarily as a result of the skewed distributions of the precipitation data. Although transformed precipitation data were back-transformed after interpolation for InterpolB, the interpolated and spatially aggregated precipitation data are still skewed and may be erroneous. In addition, the back transformation after the interpolation introduced some bias, as mentioned earlier.

The two-way chi-square test results for any difference between the four methods (Fig. 6 for 24-month SPI) agree with the findings from the time series graphs. When SimpleA was compared to InterpolA for counties and subbasins, significant differences were found (Fig. 6a). The percentages of the samples show-
ing any difference generally decrease as the spatial unit becomes large (Fig. 6a) because large spatial features involve more weather stations, and the information from nearby stations is not as important as it for small spatial features. On the other hand, the percentages of the samples showing any difference tend to increase as the spatial unit becomes large, as when SimpleB was compared to InterpolB (Fig. 6b). This is probably a result of the effect of the transformation and the back transformation of precipitation data, which is greater for large spatial features involving more weather stations.

The differences resulting from the order of procedures was also tested; SimpleA was compared to SimpleB, whereas InterpolA was compared to InterpolB (Figs. 6c,d). SimpleA and SimpleB produced significantly different results for moderate and large spatial units (Fig. 6c). As described in Fig. 4a, the effect of the 79 counties and 25 subbasins with only one weather station reduces the differences between SimpleA and SimpleB for counties and subbasins (Fig. 6c). InterpolA and InterpolB produced significantly different distributions for all spatial units (Fig. 6d).

c. Comparison of distributions at different spatial units

The empirical binned frequency distributions of drought index values using drought categories were compared using the drought index data during 1975–2004. In general, the difference was detected between small (e.g., counties and subbasins) and large spatial units (e.g., regions and subregions). Because large spatial units tend to smooth the spatial variability of drought conditions, their distributions differed from small spatial units, which, by providing more information for the region, better represent the spatial variability. Compared to large spatial units, small spatial units tend to have higher frequencies for wet and dry categories and lower frequencies for the near-normal category (Fig. 7 for PDSI).

The percent frequencies for drought categories were compared between different spatial units for all four methods. The empirical binned frequency distributions were compared between climate divisions and counties as well as between regions and subbasins in Fig. 7 for PDSI. SimpleA produced the most different distributions between different spatial units; the percent frequency in the extreme drought category for counties was higher than the value for climate divisions by about 2% for PDSI (Fig. 7a), and the value for subbasins was also higher than the value for regions by about 2% (Fig. 7e). The methods using interpolation and spatial aggregation (InterpolA and InterpolB) created relatively consistent drought index distributions between different spatial units compared to the methods using simple unweighted average (SimpleA and SimpleB), especially between climate divisions and counties (Fig. 7) and between subregions and basins (not shown).

The empirical binned frequency distributions were also compared region by region. Except for the mountains climate division in South Carolina, which cuts through counties, each climate division contains several entire counties within it. The distribution with data from each climate division was compared to the distribution with data from all counties within the climate division. Similarly, the distribution with data from each subregion was compared to the distribution with data from all subbasins within the subregion. In both cases, the observed differences were smaller compared to the differences when all climate divisions or all subregions were used.

Two-way chi-square tests were performed using 1000 samples of size 3000 resampled from the drought index data during 1975–2004 to determine the difference between various spatial units for each method. The percentages of the samples showing any difference were calculated. We assume that low percentages mean consistent information between the spatial units compared. When subregions were compared to basins, all four methods provided relatively consistent drought information (<20% for all drought indices). In general, InterpolB produced the most consistent drought information between different spatial units, whereas SimpleA showed the most different empirical binned frequency distributions (regions versus subbasins, subregions versus subbasins, basins versus subbasins, and climate divisions versus counties for all drought indices; Figs. 8a,b). When regions were compared to either subregions or basins, the methods providing the most consistent drought information differ for the tested drought index (Figs. 8c,d). SimpleA or InterpolA provided relatively consistent drought information for PDSI, PHDI, Z index, and 24-month SPI (Fig. 8c for 24-month SPI), whereas SimpleB or InterpolB provided relatively consistent drought information for 1-, 3-, 9-, and 12-month SPI (Fig. 8d for three-month SPI).

5. Conclusions

The use of spatial interpolation and aggregation of drought index values was investigated by comparing four different drought index mapping methods at different spatial units. The simple unweighted average method was compared to the interpolation plus aggregation method, which uses the selected inverse distance
weighted interpolation technique. The procedures for obtaining drought index values were also compared.

Each of the four methods behaves differently for different spatial units. For small spatial units, including nearby weather stations outside the unit causes significant differences in drought index values. The decision to perform spatial operations before or after calculating drought index values causes significant differences for moderate-to-large spatial units. The two methods that performed spatial operations of precipitation and temperature before calculating drought index values produced wetter conditions for very wet periods and drier
conditions for very dry periods for large spatial units. Although these can be considered more conservative measures, the wetter and drier conditions may be a result of the skewness of the precipitation data.

Any difference between the empirical binned frequency distributions of different spatial units was tested to determine whether or not the methods provide consistent drought information between various spatial units. In general, the method performing spatial interpolation plus aggregation of precipitation and temperature data and then calculating drought index values provides the most consistent drought information between various spatial units. However, some differences between different spatial units may indicate that mapping drought index values for small spatial units provides more information on the spatial variability of drought conditions—information not available for mapping drought index values for large spatial units.

Each method has its strengths and weaknesses. The methods using interpolation and aggregation introduce fewer errors than the simple unweighted average method based on the cross-validation RMSE and MAE statistics. These methods can produce drought index values for small spatial units, such as counties and sub-basins, even though they include no weather station. The method performing spatial interpolation plus aggregation before calculating drought index values provides the most consistent drought information between various spatial units, but it requires transformation and back transformation of precipitation data and may introduce additional errors. The method performing spatial interpolation plus aggregation after calculating drought index values can be obtained easily without these complicated procedures. The methods using simple unweighted average have much simpler procedures. However, they are not able to produce drought index values for many subbasins and counties and may cause errors when the stations are not evenly distributed or when very few stations exist within each spatial feature. Because county-level drought index values are preferred by the water systems managers of the Carolinas (K. Dow et al. 2008, unpublished manuscript) and small watershed basin-level drought index values are often required for water resources management, the information from neighboring weather stations that can be obtained by the interpolation and spatial aggregation procedures is invaluable, especially when the distribution of weather stations is not uniform.
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