Estimating Drought Conditions for Regions with Limited Precipitation Data

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ABSTRACT

Three closely related issues that affect drought estimation in regions with limited precipitation data are addressed by investigating methods for filling missing daily precipitation data, handling short-term records, and deriving drought information for unsampled locations. The analysis yields three general conclusions: 1) it is better to conduct spatial interpolation prior to calculating drought index values, 2) using weather stations with moderate lengths of records (usually at least 10 years) improves the spatial–temporal characterization of drought, and 3) alternative precipitation sources of the National Weather Service multisensor precipitation rainfall estimates and the Tropical Rainfall Measuring Mission (TRMM) satellite monthly rainfall product (3B43) do not outperform spatially interpolated daily precipitation data in most regions, except in the western United States where the TRMM-based precipitation data work better than the spatially interpolated values for drought monitoring.

1. Introduction

Drought is a natural hazard that has adverse impacts on humans and the ecosystem. Since it is a relative feature of climate and different from aridity (Wilhite and Buchanan-Smith 2005), drought occurs anywhere. However, effective drought response often requires definitions specific to a region and application of interest (Wilhite and Buchanan-Smith 2005).

There have been great efforts to monitor drought conditions using drought indices (Heim 2002), typically calculated using in situ meteorological data measured from weather stations. The two most commonly used drought indices in the United States are the Palmer drought severity index (PDSI; Palmer 1965) and the standardized precipitation index (SPI; McKee et al. 1993). The PDSI, developed by Palmer (1965) and based on a simple water balance model, uses precipitation and mean temperature data to calculate potential and actual evaporation, recharge, runoff, and loss. The PDSI has been used as an indicator of the onset and termination of drought events. The SPI was introduced by McKee et al. (1993) and measures precipitation deficit at a variety of time scales (Guttman 1998, 1999). The SPI uses only precipitation data and is appropriate for monitoring drought over large areas since the values are comparable over space and time because of the standardized transformation process (Guttman 1998, 1999).

Obviously, high-quality precipitation data play an important role in drought monitoring. While National Weather Service (NWS) Cooperative Observer Program (COOP) data provide a long and often consistent time series, making them appropriate for research and applications, these volunteer-collected data include some observer bias (Daly et al. 2007) and some missing data due to instrument failure or omitted reports (Jeffrey et al. 2001). Additionally, many stations have records too short to create a long-term climatology because the network has been extended gradually, and the distribution of weather stations is irregular and sparse in some regions. These problems hamper the direct use of in situ precipitation data for drought monitoring.

Temporal aggregation of daily precipitation data (e.g., monthly precipitation) requires a threshold for allowed number of missing days. For example, the World Meteorological Organization (WMO) recommends the 3/5 rule, which allows only up to 3 consecutive missing days or 5 total missing days for a month when 30-year normals values are calculated (WMO 1989). Months failing to satisfy this threshold remain missing and are excluded from the calculation. For drought monitoring, however, the drought condition of the month should be calculated either by estimating the missing daily data (e.g., Eischeid

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et al. 2000) or by estimating the entire month even if there exist few days of missing data. There are many methods to estimate missing daily precipitation data. In arid or semiarid regions they may be assumed to be zero (e.g., Jolly and Running 2004). Elsewhere, traditional estimation methods include spatial interpolation such as simple or weighted average of surrounding stations (e.g., Paulhus and Kohler 1952), inverse distance weighted (IDW; e.g., Rhee et al. 2008), and ordinary kriging (e.g., Jeffrey et al. 2001). Detailed descriptions of a number of spatial interpolation techniques are found in many studies, including Hartkamp et al. (1999), Lam (1983), Li and Heap (2008), and Mitas and Mitasova (1999). Data-driven methods such as an artificial neural network also have been used recently (e.g., Coulibaly and Evora 2007). For operational drought monitoring system, it is appropriate to use a simple and widely accepted method if it produces comparable results to more sophisticated ones.

Drought indices measuring departures from normal conditions (e.g., the PDSI and the SPI) require historical data longer than 30 years to examine long-term climatological averages. However, many COOP stations only have short-term records and are usually excluded from the drought monitoring network. The drought index values of the excluded stations' locations are estimated using nearby stations with long-term data. This method is acceptable if the distribution of weather stations is dense, but drought index values calculated based on the climatology of shorter-term records might be more reliable than the values from nearby stations if the distribution of weather stations is sparse. Willmott et al. (1996) compared temporal substitution (substitution from other periods) versus spatial interpolation from nearby stations of mean precipitation data to create large-scale weather station climatologies of precipitation. They concluded that using more weather stations with temporal substitution produced better results—even though they have unequal lengths of record—than using fewer stations with long and uniform periods of record. The validity of using climatological characteristics of precipitation data, such as parameters of probability distributions used for calculating SPI based on short-term records, needs to be investigated for regions with sparse weather stations.

A drought monitoring tool called the dynamic drought index tool (DDIT) has been developed for North Carolina and South Carolina (Carbone et al. 2008). The spatial interpolation of precipitation data or drought index values is appropriate for the Carolinas because of the relatively dense distribution of weather stations. This tool is being extended to larger areas including 18 eastern states with a wide range of station density, requiring further investigation of missing data issues. Prompted by the practical need for an operational drought monitoring tool, this study examines how to obtain drought information for regions with limited precipitation data. Its purpose is to find a method to handle missing daily precipitation data for drought monitoring, to decide whether to include weather stations with short-term records, and to examine the use of additional sources of precipitation data other than COOP data.

This paper is organized as follows: section 2 describes the study area and introduces in situ as well as remote sensing datasets used in this study. Section 3 explains research methods used for examining issues related to drought estimation in regions with limited precipitation data. Section 4 presents results obtained from the methods, and we conclude in section 5.

2. Study area and data

All analyses were performed using daily U.S. Historical Climatology Network (USHCN) data from the 48 conterminous United States (Fig. 1). The USHCN dataset includes daily maximum and minimum temperature, precipitation amount, snowfall amount, and snow depth from 1062 weather stations with robust long-term records—a subset of the 1221 weather stations of the monthly USHCN dataset (Williams et al. 2004). The data were obtained from National Climatic Data Center (NCDC). Since the purpose of this study is to address data shortcoming issues for drought monitoring, all comparisons and analyses were performed using the standardized and commonly used drought index: the SPI. Daily precipitation data were aggregated into monthly data, and only months with no missing data were used for the analyses to create a reference of SPI values. A 30-year period preceding 1990 (generally 1961–90) for each station and for each month was used for calibrating SPI coefficients. Those stations that do not have 30 years of nonmissing records were excluded; a total of 824 stations were used in this study. The average spatial density of weather stations is 1.02 stations per 10^4 km^2. To examine the effect of station density, 48 states were divided into four density groups of states (Fig. 1a). Each group has a similar number of weather stations and, as a result, a similar sample size (Fig. 1; Table 1). All analyses were also performed for each of the six climate regions as divided by regional climate centers (western, high plains, midwestern, Northeast, southern, and Southeast) to examine regional differences (Fig. 1b), as well as for each season [December–February (DJF), March–May (MAM), June–August (JJA), and September–November (SON)] to identify the effect of the time of year on compared methods.

Two alternative sources of precipitation data were considered: the NWS hybrid precipitation data (Seo 1998)

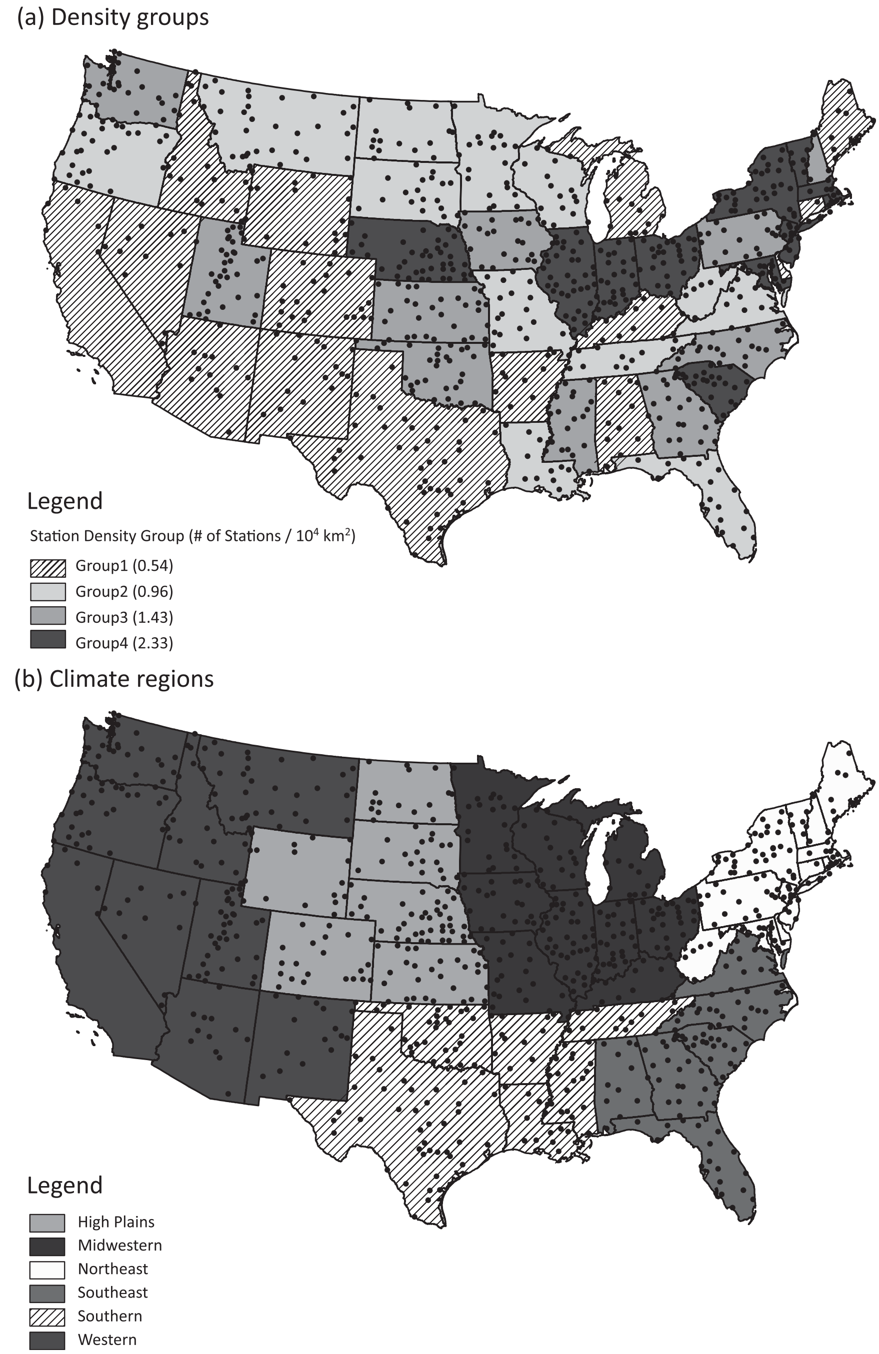

FIG. 1. The 48 conterminous United States were used and they were divided into (a) four density groups and (b) six climate regions.

and the Tropical Rainfall Measuring Mission (TRMM) satellite 3B43 "TRMM and other sources" rainfall product. The NWS hybrid precipitation data are multisensor rainfall estimates using rain gauge data and radar rainfall; estimation procedures significantly improve the accuracy of any single source (Seo 1998). The data are available from 2005 for the entire conterminous United States, but from July 2003 for the southeastern United States (mostly over the southern and Southeast climate regions). The data were obtained from the NWS River Forecast Center (http://www.srh.noaa.gov/rfcshare/p_download_new/).

The TRMM 3B43 product is the combination of the 3-hourly merged high-quality IR estimates product (3B42) using TRMM Microwave Imager (TMI) and the

TABLE 1. Four station density groups of the conterminous United States.

Density groups	No. of states	No. of stations	Avg density [No. of stations $(10^4\ km^2)^{-1}$]
Group 1	15	189	0.54
Group 2	12	210	0.96
Group 3	10	216	1.43
Group 4	11	209	2.33

precipitation radar (PR), the monthly accumulated Climate Assessment and Monitoring System (CAMS) from National Oceanic and Atmospheric Administration (NOAA)'s Climate Prediction Center, or the Global Precipitation Climatology Center (GPCC) rain gauge analysis (3A45) product (NASDA 2001; Huffman et al. 2007). This product has been proven to be useful in agricultural drought monitoring (Rhee et al. 2010). The data available from 1998 and given as monthly precipitation rate (mm h^{-1}) in 0.25° × 0.25° spatial resolution were obtained from the Goddard Distributed Active Archive Center (DAAC; ftp://disc2.nascom.nasa.gov/data/TRMM/Gridded/3B43_V6/). Since the Global Historical Climatology Network (GHCN; Vose et al. 1992) has been used for the GPCC product (Adler et al. 2003; Rudolf and Schneider 2005), and it includes common COOP stations with the USHCN, the TRMM product and the reference data are not completely independent. Nonetheless, the TRMM product was tested because it is mainly based on remote sensing data.

The NWS hybrid precipitation data and the TRMM satellite 3B43 rainfall product were selected because they have a monthly time scale and can be used directly without additional data processing. Although unused in this study, there exist satellite-based precipitation estimates independent of gauge data, including the TRMM 3-hourly merged high-quality IR estimates product (3B42 real time; Huffman et al. 2007), the Climate Prediction Center morphing algorithm (CMORPH; Joyce et al. 2004), the Passive Microwave-Calibrated Infrared algorithm (PMIR; Kidd et al. 2003), and the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Network (PERSIANN; Sorooshian et al. 2000). The use of these products for estimating drought conditions remains for future research.

3. Methodology

We examine three separate but closely related issues associated with drought estimates in regions with limited precipitation data: handling missing data, inclusion of weather stations with short-term records, and the usefulness of other precipitation sources. As reference data for all three issues, SPI values were calculated using months without any missing precipitation days.

a. *Missing daily precipitation data*

Three methods compared for dealing with missing daily precipitation data are listed below:

1) METHOD1–1: SPI values are spatially interpolated from nearby stations.
2) METHOD1–2: Missing daily precipitation data are spatially interpolated from nearby stations, and then SPI values are calculated.
3) METHOD1–3: Missing daily precipitation data are filled with long-term historical daily normals, and then SPI values are calculated.

For the comparisons, only months without missing daily precipitation data during 1991–2000 were identified, and then the missing days were randomly generated for each month and each station. To examine the effect of the number of missing days, missing days of 5, 10, 15, 20, 25, and all (28–31, according to the month) per month were tested respectively for METHOD1–2 and METHOD1–3 (e.g., when 3-month SPI values are compared with 5 missing days per month, a total of 15 missing days are randomly generated for METHOD1–2 or METHOD1–3).

The IDW method was used for the spatial interpolation of SPI values for METHOD1–1 and daily precipitation data for METHOD1–2. The IDW was selected because of its simplicity and ease of use; despite its simple form, it often performs as well as complicated methods such as Kriging (e.g., DeGaetano and Belcher 2007; Dirks et al. 1998; Rhee et al. 2008; Tabios and Salas 1985). The values of unsampled locations are estimated from the nearby sample points weighted by the distances between them:

$$Z_j = \left(\sum_i \frac{Z_i}{d_{ij}^n}\right) \Big/ \left(\sum_i \frac{1}{d_{ij}^n}\right), \tag{1}$$

where Z_j is the estimated value for the unsampled point j, Z_i is the value for the sampled point i, d_{ij} is the distance between two points i and j, and n is the power parameter. The search radius was determined as 100 km, considering the weather station density of the USHCN dataset. On average, a circle with a radius of 93.80 km includes about five nearby stations. The typical power parameter value of 2 was used. Since geographic coordinates were used, distances between two points were calculated using the Vincenty formula (Vincenty 1975).

These methods were compared using the cross-validation mean absolute error (MAE), since the magnitudes of drought index values are significant for triggering appropriate drought responses (Quiring 2009). The MAE is also known better than the root-mean-square error (RMSE) for assessing average model performance (Willmott and Matsuura 2005). The correlation coefficient r and the index of agreement d between observed (reference data) and estimated values were also obtained to support the results based on MAE. The index of agreement d proposed by Willmott (1981, 1982) can be used with traditional correlation measures such as the correlation coefficient r and difference measures of MAE by providing information on the relative average error. It is defined as

$$d = 1 - \left[\sum_{i=1}^{N} (P_i - O_i)^2 \Bigg/ \sum_{i=1}^{N} (|P_i'| + |O_i'|)^2 \right], \qquad (2)$$

where $P_i' = P_i - \overline{O}$ and $O_i' = O_i - \overline{O}$. It ranges from 0 (no correlation) to 1 (perfect fit).

b. *Short-term records*

When monitoring drought, one should decide whether to include only weather stations with lengthy and temporally commensurate time series, or to supplement such records with other stations with shorter records in order to improve the spatial resolution of stations. Prior studies suggested that the within-station substitution performs better than the spatial interpolation for representing spatial–temporal variability of large-scale climatology, such as time-averaged precipitation (Willmott et al. 1996). Since calculating some drought index values requires data of 30 years or longer, typically only limited weather stations with a long history have been included for drought index mapping. However, Willmott et al. (1996) noted that stations with a moderate length of history (about 10 years) may represent the climatology (drought condition in this case) of the locations better than nearby stations.

To this end, spatially interpolated SPI values from nearby stations were compared to the values calculated at their location using SPI climatological coefficients based on their short-term records. This analysis helps to determine whether to include weather stations with short-term records for better describing spatial distributions of drought conditions. Compared were the SPI values based on short-term records of 5, 10, 15, 20, and 25 years (with periods ending in 2000; for example, the period for short-term records of 10 years is 1991–2000) and the spatially interpolated SPI values using nearby stations to the observed SPI values calculated 30 years of data (reference data) for the period of 1996–2000. Two methods were compared:

1) METHOD2–1: SPI values are spatially interpolated from nearby stations.
2) METHOD2–2: SPI values are calculated based on short-term records of 5, 10, 15, 20, and 25 years.

c. *Unsampled locations*

If there are more accurate precipitation data available (than the spatially interpolated values from nearby stations), drought index values can be calculated using alternative precipitation data sources. Two such sources were considered: the NWS hybrid precipitation data and the TRMM 3B43 "TRMM and other sources" rainfall product. Two methods for each product were compared at the weather stations' locations assuming all data are missing:

1) METHOD3–1: Missing daily precipitation data are spatially interpolated from nearby stations, and then SPI values are calculated.
2) METHOD3–2: Missing daily precipitation data are filled with precipitation data from the alternative data source (NWS or TRMM), and then SPI values are calculated.

Direct comparisons between gridded data and data from weather stations are not recommended because of the discrepancy in spatial resolutions. In this case, station data may be gridded using various methods such as station average (e.g., Hand and Shepherd 2009) and Thiessen polygon (e.g., Han et al. 2010). In this study, however, the main interest is to examine the use of precipitation data from alternative sources for obtaining drought index values at unsampled locations, compared to spatially interpolated precipitation data typically used for this purpose. Thus, rather than upscaling station data, SPI values calculated based on the two different methods listed above were evaluated based on the reference data at the weather stations' locations, and the performance was compared to the SPI values based on the spatially interpolated daily precipitation data.

The NWS hybrid precipitation data were obtained in Environmental Systems Research Institute, Inc., (ESRI) Shapefile format, with grid points in the Hydrologic Rainfall Analysis Project (HRAP) grid coordinate system. Grid points located closest to the USHCN stations were selected for the analyses. To use a longer period of data for calculating coefficients for SPI, only data in the southeastern United States (with 254 USHCN stations) were used. The SPI values for each grid point were calculated for the period of July 2003–December 2008 (thus coefficients for SPI calculations are also based on this period), and they were compared with the reference data for the period of July 2003–December 2005 (the USHCN daily data are only available until 2005).

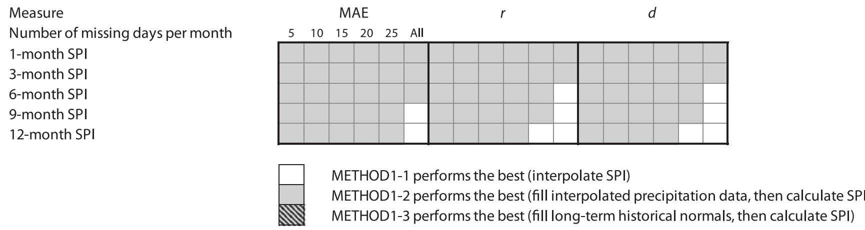

FIG. 2. Comparisons of three methods for filling missing daily precipitation data.

The monthly TRMM data were imported into ERDAS, Inc., Imagine format and all month layers from January 1998 to December 2007 were stacked using ERDAS Imagine software. The values for the grid points closest to the USHCN stations were obtained using the customized intersection tool developed by Im (2006), embedded in ESRI ArcGIS using Visual Basic. Using the 10 years of data, the coefficients for SPI were obtained for each grid. Then, SPI values were calculated and compared to the reference data for the period of 1999–2005, since the 12-month SPI can have data from 1999 and the USHCN daily data are available until 2005.

4. Results and discussion

a. Missing daily precipitation data

In general, it is most appropriate to fill missing daily precipitation data by spatial interpolation and then calculate SPI values (METHOD1–2). The interpolated SPI values (METHOD1–1) only performed better for 9- and 12-month SPI when all data were missing based on the cross-validation MAE. The correlation coefficient r and the index of agreement d produce generally similar results (Fig. 2). The threshold numbers of missing days differentiating the best methods between the two (METHOD1–1 and METHOD1–2) vary with the time scale of SPI and the statistical measure, and they tend to decrease with the increased time scale of SPI (Fig. 2). METHOD1–3 could not outperform other methods in any case.

Although many applications using daily precipitation data allow few missing days, the results indicate that the estimated SPI values can be closer to the actual values when the missing daily precipitation data are filled with spatially interpolated values from nearby stations even when all data are missing for 1–6-month SPI, and up to 25 days per month for 9- and 12-month SPI. As examples, the cross-validation MAE values between the estimated SPI values and the reference data for 9-month SPI averaged over the study area are presented in Fig. 3 and some of their spatial distributions are shown in Fig. 4. When the number of missing days is up to 25 days per month, METHOD1–2 (e.g., MAE = 0.21, sample size n = 56 683 for 5 missing days per month) outperformed METHOD1–1 (MAE = 0.53, n = 54 197) and

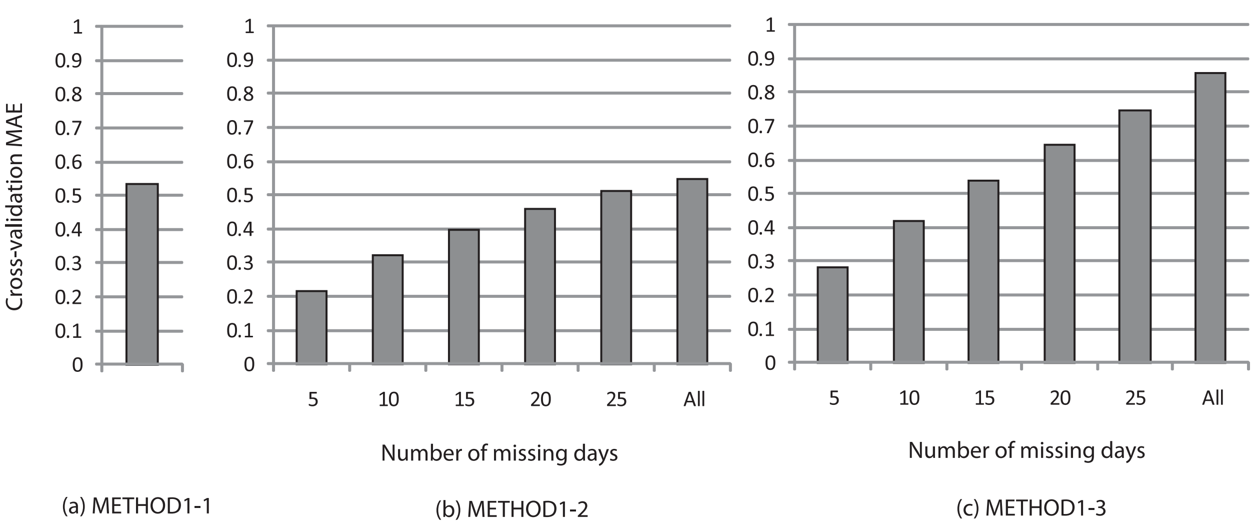

FIG. 3. Cross-validation MAE values between the estimated SPI values and the reference data of each method for 9-month SPI averaged over the study area.

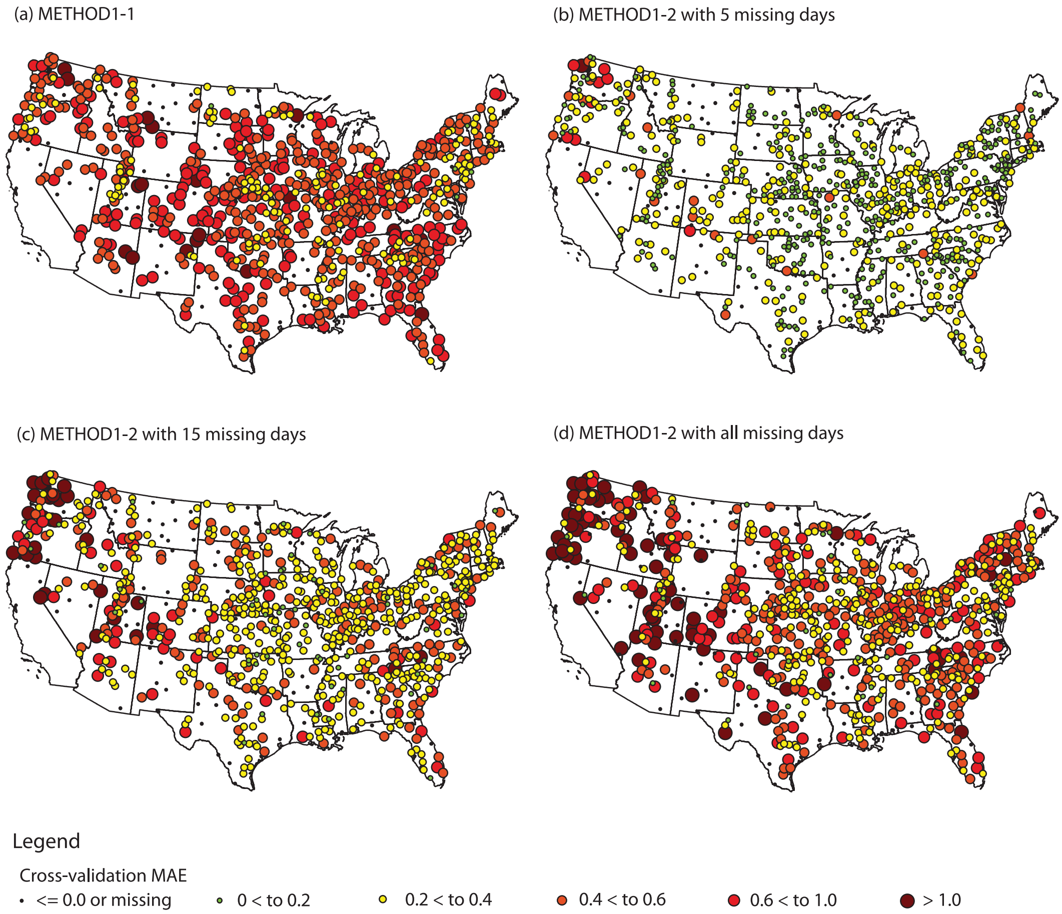

FIG. 4. Spatial distributions of the cross-validation MAE values between the estimated SPI values and the reference data for 9-month SPI using (a) METHOD1–1, (b) METHOD1–2 with 5 missing days, (c) METHOD1–2 with 15 missing days, and (d) METHOD1–2 with all missing days.

METHOD1–3 (e.g., MAE = 0.28, n = 62 033 for 5 missing days per month), while METHOD1–1 has the lowest MAE value when all data were missing (Fig. 3).

The spatial distributions of MAE values provide additional information on regional differences (Figs. 4a,d). While METHOD1–1 slightly outperformed METHOD1–2 for 9-month SPI when all data were missing based on the cross-validation MAE values averaged for the study area (Figs. 1 and 2), large MAE values of METHOD1–2 are mainly observed for the weather stations located in the western states (Fig. 4d). Stations with missing MAE values occurred when there were no neighboring stations within the 100-km search radius (Fig. 4). The sample size varies because the days with missing precipitation data for each month and for each station were randomly generated, with the number of missing days fixed as 5, 10, 15, 20, 25, and all.

The analyses were also done for four density groups (Fig. 1a), six climate regions (Fig. 1b), and four seasons (Fig. 5). The most noted are the results for climate regions, especially the differences between the western climate region and other areas (Fig. 5b). While METHOD1–2 performed the best for SPI of all time scales with any number of missing days in the high plains, midwestern, Southeast, and southern climate regions, and for SPI of longer time scales with large numbers of missing days in the Northeast climate region, METHOD1–1 showed smaller MAE values than METHOD1–2 for SPI of relatively short time scales with smaller numbers of missing days (from 20 days per month) in the western climate region (Fig. 5b). Although not shown in Fig. 5, METHOD1–3 even produced smaller MAE values than METHOD1–2 for 6-month SPI with 20 missing days and 9- and 12-month SPI with missing days from 20 to all. The different results of the western climate region can be explained by the high elevation of the region; while IDW is only dependent on distances between the sampled and estimated points and may not be sufficient for interpolating precipitation data in mountainous regions, it may be acceptable for

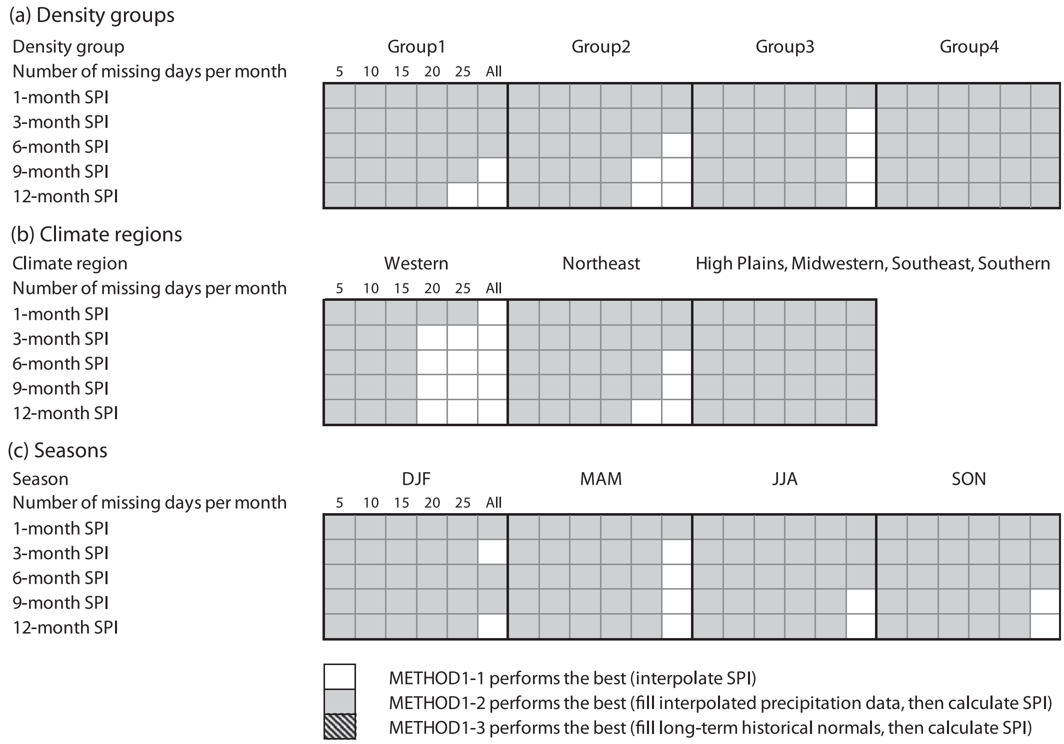

FIG. 5. Comparisons of three methods for filling missing daily precipitation data for (a) four density groups, (b) six climate regions, and (c) four seasons using the cross-validation MAE values.

interpolating SPI values since they are standardized for each location and therefore comparable over space.

There was no specific tendency found for density groups and seasons (Figs. 5a,c); the results for four density groups seem to be affected by the locations of the states belonging to each group (Figs. 1a,b and 5a).

b. *Short-term records*

The SPI values based on short-term records (METHOD2–2) generally produced smaller cross-validation MAE values than the spatially interpolated SPI values (METHOD2–1) when the lengths of records were equal or longer than 10 years (10, 15, 20, and 25 years) for all SPI time scales (Fig. 6a for 3-month SPI). The cross-validation MAE values decreased significantly with the length of records (Fig. 6a). The correlation coefficient *r* values of METHOD2–2 were larger than the values of METHOD2–1 even when the lengths of records were only 5 years and the index of agreement *d* values behaved almost the same (Figs. 6b,c for 3-month SPI), except for 1-month SPI with 5 years of records (data not shown).

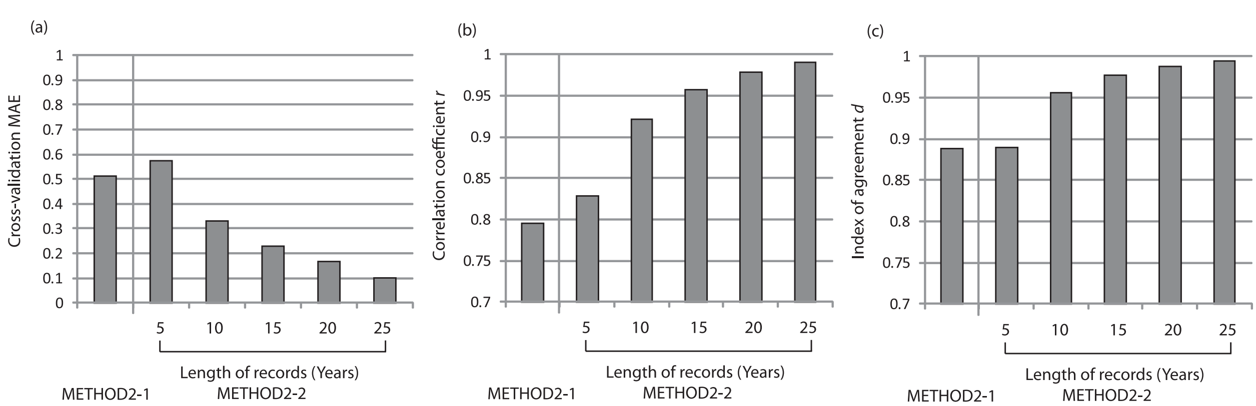

FIG. 6. Comparisons of (a) the cross-validation MAE, (b) the correlation coefficient *r*, and (c) the index of agreement *d* between the estimated 3-month SPI values using two methods and the reference data.

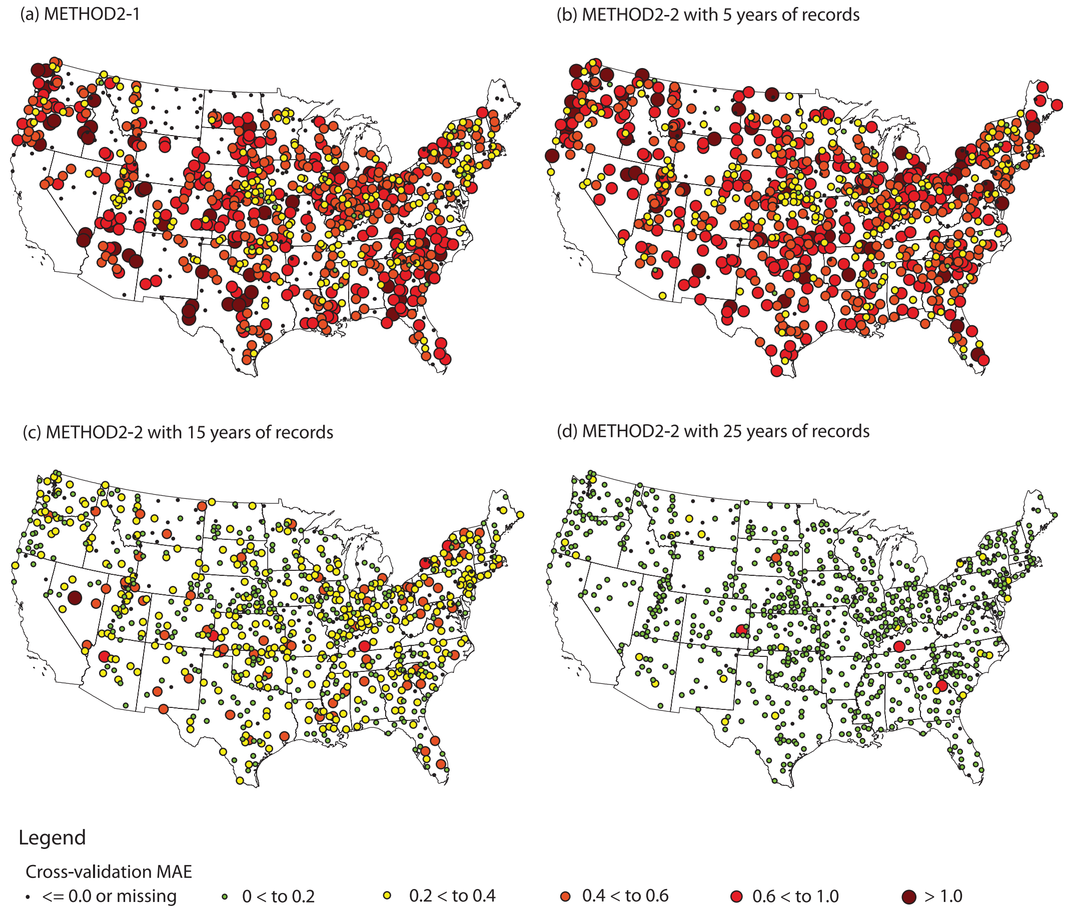

FIG. 7. Spatial distributions of the cross-validation MAE values between the estimated SPI values and the reference data for 12-month SPI using (a) METHOD2–1, (b) METHOD2–2 with 5 years of records, (c) METHOD2–2 with 15 years of records, and (d) METHOD2–2 with 25 years of records.

The cross-validation MAE did not show significantly different results for four density groups. When six climate regions were compared, the SPI values calculated with as few as 5 years of records produced smaller MAE values than the spatially interpolated values for 9- and 12-month SPI in the Southeast climate region, and for 6–12-month SPI in the high plains climate region (data not shown). The spatial distributions of the cross-validation MAE values for 12-month SPI are shown in Fig. 7. The results from the seasonal analyses indicate that the SPI values calculated with only 5 years of records have smaller MAE values than the spatially interpolated values for 1- and 3-month SPI for JJA only (data not shown).

It may be meaningful to use a consistent number of robust stations with lengthy and temporally commensurate time series in climate change studies. However, these results from the analyses using short-term records show how including as many stations with moderate lengths of records (perhaps at least 10 years) can improve the representation of spatial–temporal variability of drought.

c. Unsampled locations

Based on the findings about filling missing daily precipitation data for drought index estimation, the best way to obtain drought index values for stations with missing days is generally to estimate precipitation data for each location from nearby stations, and then to obtain the drought index values based on the estimated precipitation values. In this section, SPI values were calculated using the NWS hybrid precipitation data and the TRMM rainfall data respectively, and then compared to the performance of the SPI values calculated based on the precipitation data spatially interpolated from nearby stations with respect to the reference data.

Neither the NWS hybrid precipitation data nor the TRMM-based SPI values could perform better than the interpolated SPI values based on in situ data in terms of the cross-validation MAE, the correlation coefficient *r*, and the index of agreement *d* when evaluated using the averaged values over the study area (see Table 2 for the

TABLE 2. Comparisons of the cross-validation MAE values between the reference data and the SPI values obtained from the NWS hybrid precipitation data, the spatial interpolation in the southeastern United States (using 254 stations), the TRMM data, the corrected TRMM data (using 247 stations for validation, which is 30% of the total), and the spatial interpolation for the study area (824 stations; sample sizes are in parentheses).

Time scale	Cross-validation MAE between the reference data and the SPI values obtained from				
	NWS hybrid precipitation	Spatial interpolation	TRMM	Corrected TRMM	Spatial interpolation
1-month SPI	0.64 (6091)	0.40 (6473)	0.63 (55 694)	0.56 (14 323)	0.42 (50 522)
3-month SPI	0.64 (4944)	0.43 (5512)	0.63 (48 951)	0.57 (12 304)	0.48 (43 941)
6-month SPI	0.64 (3812)	0.44 (4695)	0.64 (42 418)	0.59 (10 334)	0.53 (37 706)
9-month SPI	0.65 (2960)	0.45 (4137)	0.64 (37 670)	0.60 (8915)	0.55 (33 242)
12-month SPI	0.66 (2297)	0.46 (3731)	0.63 (34 186)	0.62 (7837)	0.58 (29 989)

cross-validation MAE values). The western climate region, however, showed different results for the TRMM product; the TRMM-based 3- and 6-month SPI values produced smaller MAE values (MAE = 0.63, n = 8848 for 6-month SPI) than the interpolated SPI values (MAE = 0.85, n = 7185 for 6-month SPI). In terms of the correlation coefficient r and the index of agreement d values, the TRMM-based SPI values were closer to the reference data for 3–12-month SPI (data not shown). As observed in the comparisons between METHOD1–1 and METHOD1–2, the results in the western climate region seem to be caused by the high elevation of the region making it difficult to spatially interpolate daily precipitation data. Density groups 2 and 3 showed similar results, presumably because of locations in western states.

The poor estimation of the SPI values based on the NWS hybrid precipitation data and the TRMM product in other cases may be explained by the short record length (5.5 years) and the coarse spatial resolution (0.25° × 0.25°). Although the test results for short-term records (METHOD2–1 and METHOD2–2) showed that the SPI values based on short-term records could be estimated better than the interpolated values—even with 5 years of data—when evaluated with the cross-validation MAE values, the 5.5 years of records from July 2003 to December 2008 used for obtaining the parameters for SPI failed to produce SPI values outperforming the SPI values based on the spatially interpolated daily precipitation.

Discrepancies between TRMM data and in situ precipitation measurements may explain the poor performance. Thus, an additional analysis was done wherein the TRMM-derived values were corrected using in situ precipitation measurements. In this correction, the residuals of precipitation data (estimated precipitation data by TRMM-observed in situ precipitation data) were spatially interpolated using 70% of weather stations in the study area, and then the precipitation data of the remaining 30% of weather stations (247 weather stations) were subtracted with the amount of the interpolated residuals. Then, SPI values were calculated using the corrected TRMM precipitation data and were compared with the reference SPI values:

$$\text{residual} = \text{TRMM precipitation} - \text{in situ precipitation, and} \quad (3)$$

$$\text{corrected TRMM precipitation} = \text{TRMM precipitation} - \text{spatially interpolated residual.} \quad (4)$$

The estimation was improved (the cross-validation MAE decreased and the correlation coefficient r values and the index of agreement d values increased), but still could not perform better than the spatial interpolation of the in situ SPI values in most cases. The spatial distributions of the cross-validation MAE values for 6-month SPI are shown in Fig. 8. Large MAE values in the western climate region are notable for METHOD3–1.

5. Conclusions

This study addressed data shortcoming issues for drought index estimation, and investigated various methods for filling missing daily precipitation data, handling short-term records, and obtaining drought information for unsampled locations.

Finding the most appropriate method for filling missing daily precipitation data is important in most climatological studies. The best strategy is to spatially interpolate missing daily precipitation data from nearby stations and then calculate SPI values. The threshold number of missing days tends to decrease with the time scale of SPI. The western climate region produced different results from other regions because of the effect of its high elevation; the spatially interpolated SPI showed smaller MAE values than the SPI values based on the spatially interpolated daily precipitation data with missing days longer than 20 for 3–12-month SPI. Based on this result, the 3/5 rule of WMO is generally appropriate but a

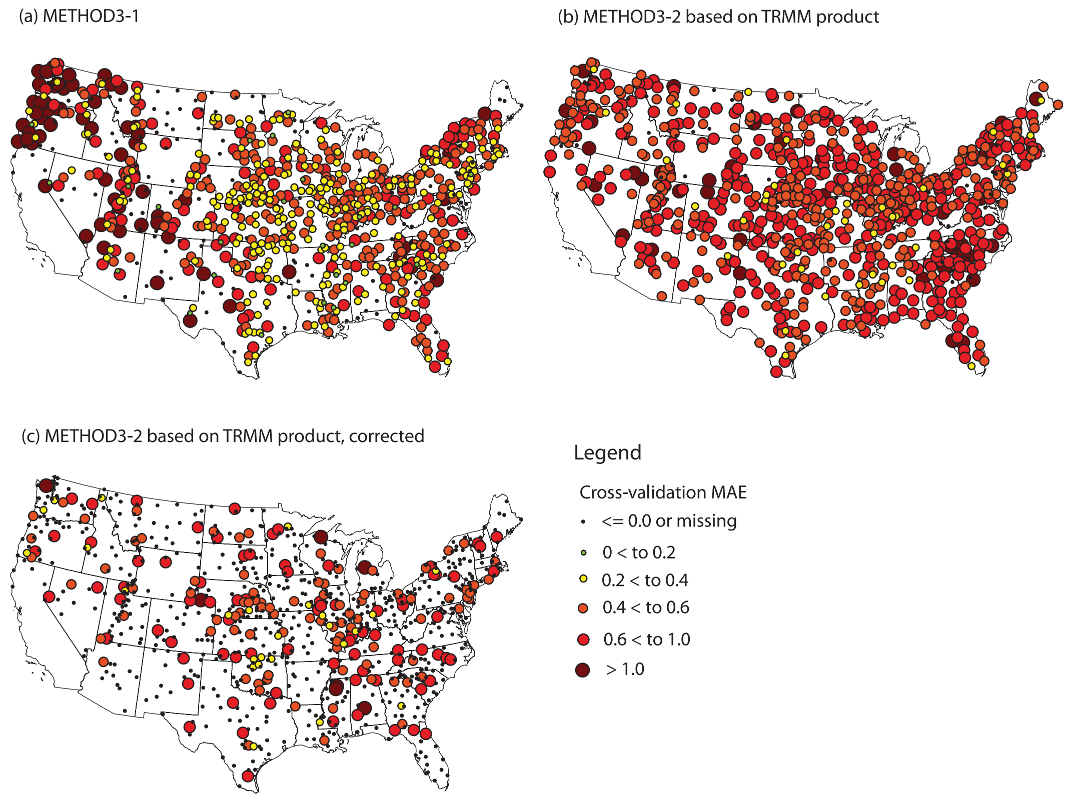

FIG. 8. Spatial distributions of the cross-validation MAE values between the estimated SPI values and the reference data for 6-month SPI using (a) METHOD3–1, (b) METHOD3–2 based on TRMM product, and (c) METHOD3–2 based on TRMM product after correction.

somewhat more lenient rule may be applied, especially in nonmountainous regions.

Including weather stations with short-term records (usually at least 10 years) could improve the representation of the spatial–temporal variability of drought conditions. Traditionally, only weather stations with long-term historical records have been used for drought monitoring. However, our results suggest that supplementing these long-term records with additional weather stations may provide more accurate drought estimates.

The drought index values based on the NWS hybrid precipitation data and the remotely sensed precipitation data from TRMM could not outperform the spatially interpolated daily precipitation values in most regions. Only the western climate region showed that the use of TRMM-based precipitation produced smaller MAE values than the spatially interpolated daily precipitation data. The use of those precipitation sources, however, may improve drought monitoring with longer records and enhanced spatial resolution through remote sensing techniques such as data fusion. Our tests demonstrate the possibility of the use of precipitation data from other sources for drought monitoring for areas without any in situ measurements.

Various tests with limited precipitation data were performed for estimating drought index values. Although similar tests may be required for each application when used for other than drought studies or outside the United States, the results obtained for the conterminous United States in this study provide useful guides for researchers. The implications obtained in this work are practical and are recommended to be used for drought studies, especially for the conterminous United States.

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