ANALYSIS OF SPATIAL PERFORMANCE OF METEOROLOGICAL DROUGHT INDICES

A Thesis

by

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ABSTRACT

Meteorological drought indices are commonly calculated from climatic stations that have long-term historical data and then converted to a regular grid using spatial interpolation methods. The gridded drought indices are mapped to aid decision making by policy makers and the general public. This study analyzes the spatial performance of interpolation methods for meteorological drought indices in the United States based on data from the Co-operative Observer Network (COOP) and United States Historical Climatology Network (USHCN) for different months, climatic regions and years. An error analysis was performed using cross-validation and the results were compared for the 9 climate regions that comprise the United States.

Errors are generally higher in regions and months dominated by convective precipitation. Errors are also higher in regions like the western United States that are dominated by mountainous terrain. Higher errors are consistently observed in the southeastern U.S. especially in Florida. Interpolation errors are generally higher in the summer than winter.

The accuracy of different drought indices was also compared. The Standardized Precipitation and Evapotranspiration Index (SPEI) tends to have lower errors than Standardized Precipitation Index (SPI) in seasons with significant convective precipitation. This is likely because SPEI uses both precipitation and temperature data in its calculation, whereas SPI is based solely on precipitation.

There are also variations in interpolation accuracy based on the network that is used. In general, COOP is more accurate than USHCN because the COOP network has a higher density of stations. USHCN is a subset of the COOP network that is comprised of high quality stations that have a long and complete record. However the difference in accuracy is not as significant as the difference in spatial density between the two networks. For multiscalar SPI, USHCN performs better than COOP because the stations tend to have a longer record.

The ordinary kriging method (with optimal function fitting) performed better than Inverse Distance Weighted (IDW) methods (power parameters 2.0 and 2.5) in all cases and therefore it is recommended for interpolating drought indices. However, ordinary kriging only provided a statistically significant improvement in accuracy for the Palmer Drought Severity Index (PDSI) with the COOP network. Therefore it can be concluded that IDW is a reasonable method for interpolating drought indices, but optimal ordinary kriging provides some improvement in accuracy.

The most significant factor affecting the spatial accuracy of drought indices is seasonality (precipitation climatology) and this holds true for almost all the regions of U.S. for 1-month SPI and SPEI. The high-quality USHCN network gives better interpolation accuracy with 6-, 9- and 12-month SPI and variation in errors amongst the different SPI time scales is minimal. The difference between networks is also significant for PDSI. Although the absolute magnitude of the differences between interpolation with COOP and USHCN are small, the accuracy of interpolation with COOP is much more spatially variable than with USHCN.

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1. INTRODUCTION

1.1 Introduction

Drought is a recurring climatic phenomenon that can have a significant impact on the environment and human life (deMenocal 2001). Bryant (1991) compared different natural hazards based on key characteristics such as severity, length, and total areal extent and demonstrated that drought is one of the most serious natural hazards. The economic impacts of drought have been documented in a number of different studies. For example, drought conditions that occurred during 2009 across parts of the Southwest U.S., Great Plains, and southern Texas caused agricultural losses in numerous states (TX, OK, KS, CA, NM, AZ) exceeding $5 billion (2009 values) (Lott et al. 2010). It is estimated that droughts cause an average of $6 to 8 billion (1995 values) in losses per year in the United States (FEMA 1995). Ross and Lott (2003) calculated that droughts accounted for 41% of estimated $349 billion (2002 values) in losses caused by weather disasters in the United States between 1980 and 2003.

Decision makers who are responsible for taking action during a drought rely on quantitative drought information from multiple sources to understand the severity and spatial extent of drought. An example of an interactive system that disseminates quantitative drought information is the drought data viewer provided by the National Integrated Drought Information System (http://drought.gov). An accurate representation of the drought conditions that can be readily understood by people with different levels of technical expertise helps ensure efficient utilization of resources during drought response. There are many challenges to providing decision makers with an accurate representation of drought conditions. This includes aggregating current weather data from different sources, qualitatively and quantitatively combining different drought indices, accounting for missing values, and interpolating to a continuous grid using spatial interpolation methods. Creating drought monitoring products involves different sources of error such as observational error, function fitting error, and spatial interpolation error. Spatial interpolation error is important because it influences the accuracy of local drought information and how decision makers use and interpret gridded drought indices.

Multiple techniques exist to overcome the issues mentioned above. Sometimes when local information is lacking:

1. The lack of weather observations can be partly addressed by using remotely sensed data.

2. Additional low-cost weather stations can be deployed and configured to provide real-time updates wirelessly. (e.g., devices manufactured by private vendor ambient weather).

3. Spatial accuracy can be improved by augmenting information from private and independent sources such as private airports, volunteer networks etc.

Interactive WebGIS-based dynamic applications are being increasingly used to disseminate real-time climate and drought information around the world (Wei et al. 2009). These applications depict the current drought conditions for a particular region as well as give the user options to interactively change the temporal resolution, time period, and other parameters that are being depicted. Other customized information can also be provided to create a rich user experience (Carbone et al. 2008). The widespread use and availability of gridded spatial data makes it important to quantify the accuracy of different interpolation methods so that users understand their limitations.

Drought or excessive moisture measures (commonly referred to simply as drought indices) are primarily based on historical climatic records at a particular location. The historical record allows for identifying the frequency of extreme events (Hayes 2002). For example, a water planner may use historical precipitation record to design a reservoir for various drought scenarios. Different drought indices are used to measure different representations of moisture. A drought index such as the Standardized Precipitation Index (SPI) is based solely on precipitation and measures moisture as a function of precipitation for a given duration vis-à-vis normal precipitation at that location. Indices such as Palmer Drought Severity Index (PDSI) and Standardized Precipitation and Evapotranspiration Index (SPEI) use the difference between precipitation and potential evapotranspiration as an indicator of moisture conditions. Multiple drought indices are needed to represent drought on different time scales.

A representation of moisture conditions in the form of a near real-time map is shown in Figure 1.1. This representation requires data assimilation from multiple sources. Figure 1.1 shows the current drought conditions across the world as generated by the University College London Drought Monitor. Although the map depicts global moisture conditions, its spatial accuracy varies from location to location and is influenced by a number of factors, including quality of source data, length of temporal record, duration under consideration, and the climatic region.

The accurate depiction of moisture conditions using maps is important because many stakeholders, decision makers and others rely on drought index maps as a primary source of information. The accuracy of these maps is primarily influenced by the accuracy of interpolation of drought indices, the observational error at a station and how accurately the drought index represents the actual conditions at a station. Different drought indices have their own advantages and disadvantages and each index may not represent the drought conditions at every location correctly (Vicente-Serrano 2008). The Palmer Drought Severity Index is not designed to handle seasonal variation in vegetation or frozen soil (Karl et al. 1987). The SPI does not account for the influence of temperature (Vicente-Serrano et al. 2010) and this shortcoming neglects the effects of water demand and evapotranspiration on drought conditions. The Standardized Precipitation and Evapotranspiration Index is a relatively new index (Vicente-Serrano et al. 2010) and there are not many studies concerning its suitability vis-à-vis SPI and PDSI. It is important to understand the influence of the three sources of errors and although they cannot be eliminated completely, an attempt to understand their magnitude and prevalence will be helpful in decision-making. There are various ways to quantify and correct for observational errors (NCDC 2007; Xie and Arkin 1996). A mechanism to quantify the spatial accuracy and use of a performance metric such as normalized absolute error can help in identifying the most accurate approach (Isaaks and Srivastava 1989).

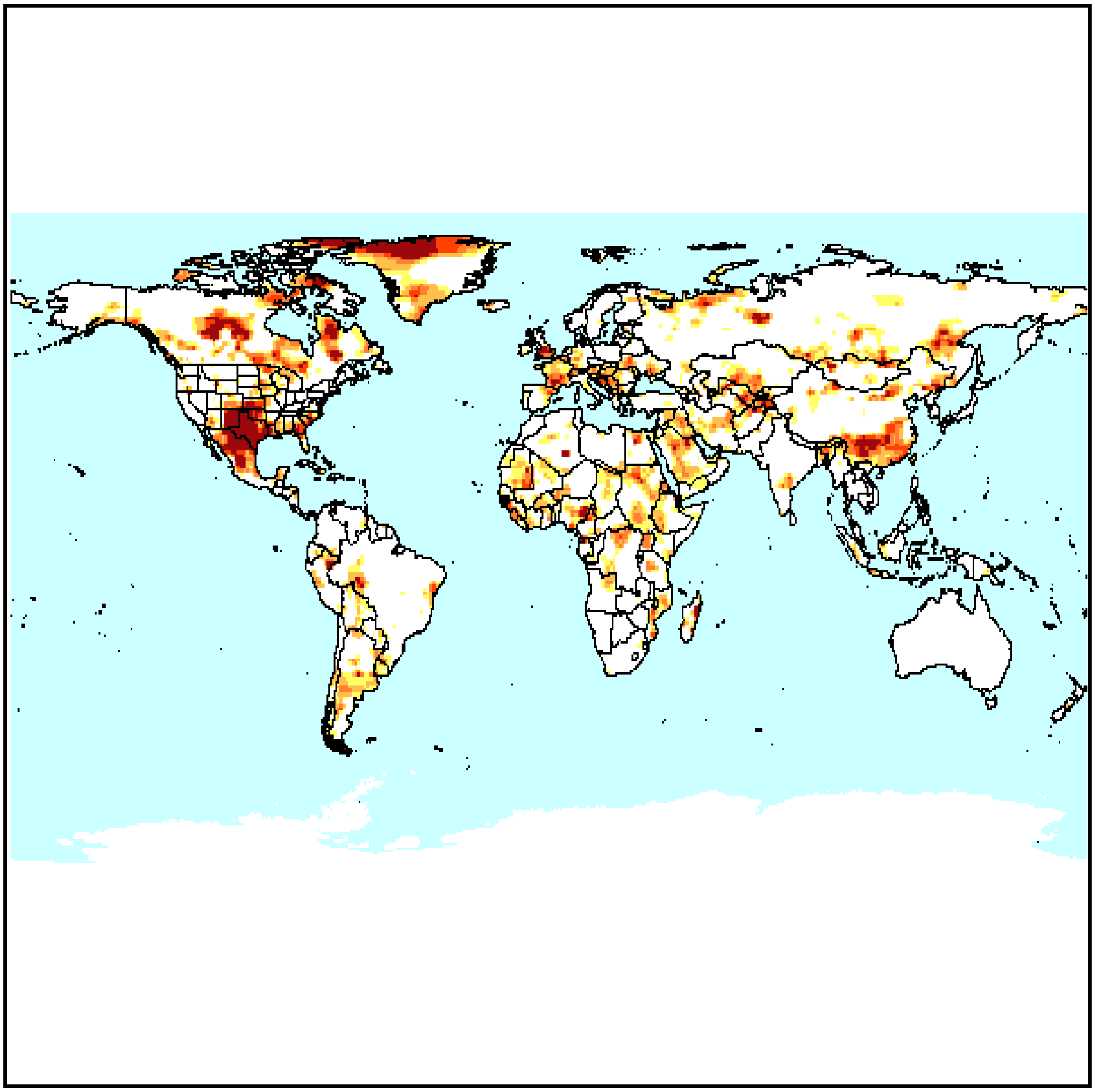

Figure 1.1 Global drought monitor: Annual (12-month) drought conditions across the world in November 2011. (University College – London, 2011)

1.2. Study Objectives

This study uses leave out one cross-validation to examine the spatial performance of different drought indices under a comprehensive set of conditions. The cross-validation technique involves comparing predicted values with actual values by iteratively removing one station at a time and using the remaining stations to predict the value at the missing station. The goal of this study is to use large datasets that cover a broader and more diverse area than has been considered in the past to examine the spatial performance of drought indices. The calculation of interpolation errors over different months, multiple years and in different climatic regions will enable us to derive answers to many other relevant questions concerning spatial accuracy. The spatial extent of this study is the contiguous United States. The two primary datasets that are utilized are the United States Historical Climatology Network (USHCN) and the National Weather Service's Co-operative Observing Network (COOP).

The primary objectives of this research are:

1. Quantify the accuracy of IDW and kriging and determine which is most suitable for interpolating different drought indices.

2. Compare the relative interpolation accuracy of three drought indices (PDSI, SPI and SPEI) using normalized errors.

3. Assess seasonal variations in the accuracy of drought index interpolation by comparing interpolation errors for January, July and October.

4. Assess the spatial variability of interpolation accuracy by comparing the mean accuracy over 9 climatic regions.

5. Compare the performance of interpolation using USHCN and COOP to illustrate the influence of spatial density of stations on interpolation accuracy.

2. BACKGROUND

2.1 Drought Indicators

A drought indicator is calculated using data such as precipitation or soil moisture to provide a measure of the moisture conditions at a location. Drought indicators are calculated with respect to normal moisture conditions.

Figures 2.1 and 2.2 depict the variation of August precipitation and precipitation departure from normal at Houston Intercontinental airport from 1969 to 2010. The precipitation departure from normal can be considered a drought indicator.

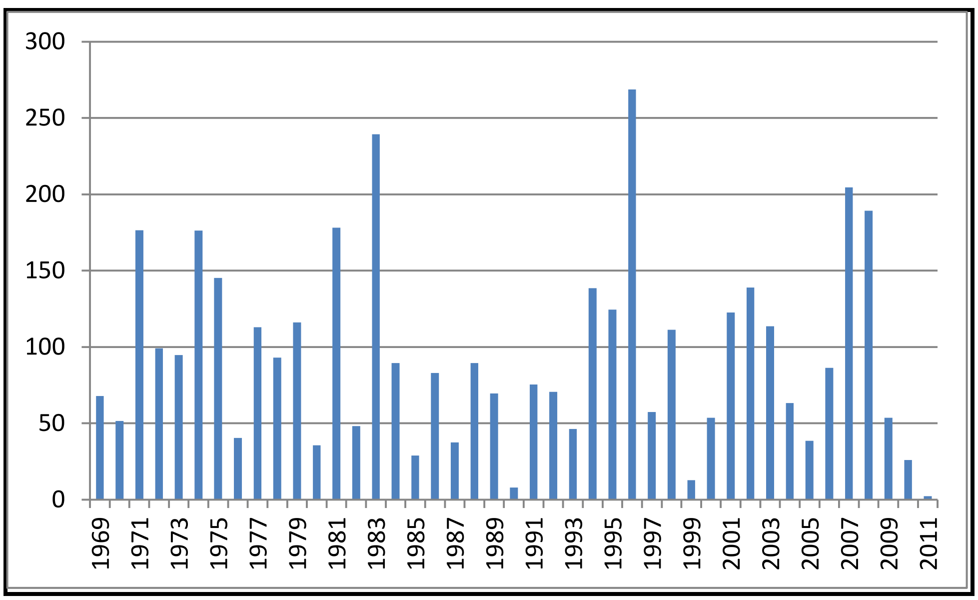

Figure 2.1 August precipitation (mm) for Houston IAH (1969-2011); (NCDC, 2011)

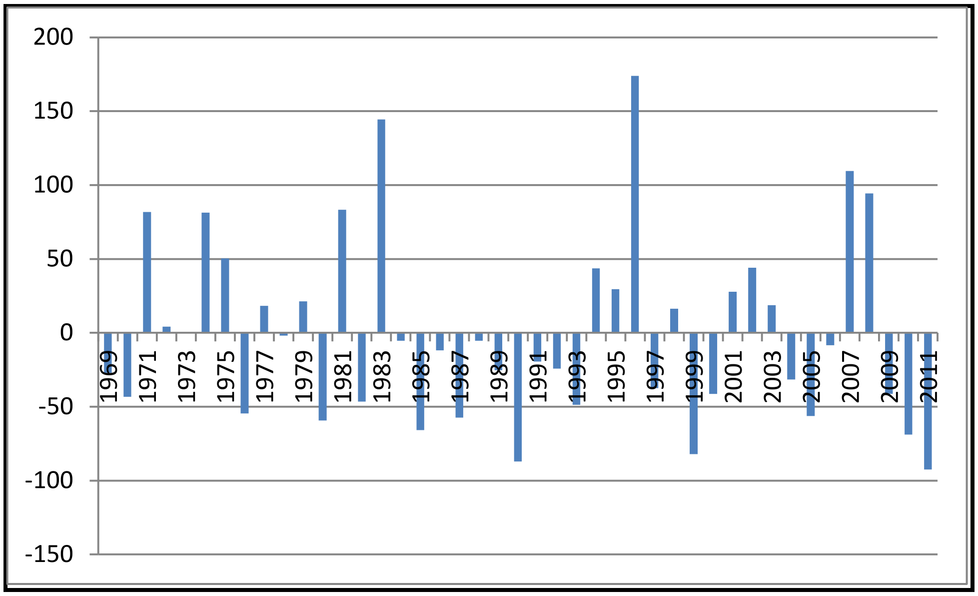

Figure 2.2 August precipitation (mm) departures from normal (1969-2011) for Houston IAH; (NCDC 2011)

A lot of information about moisture values can be inferred from Figure 2.1 and Figure 2.2, but it is important to understand that this information is not sufficient for monitoring moisture conditions. For example, precipitation departures from normal cannot be compared spatially because such departures may be more common at some locations than others. Moisture indices are defined so that we can compare the moisture conditions (or their departure from normal conditions) across spatial regions and across different seasons. This is done by using historical data at a particular location for a certain time period (week, month, and year) to get normal values, their frequency of occurrence and quantify the departure from normal using this historical data.

2.2 Meteorological Drought Indices

There is no uniform method to characterize drought conditions and there are a variety of drought indices that can be used as tools to monitor meteorological drought (Quiring 2009). The input variables required for the calculation of meteorological drought indices vary depending on the drought index in question, but include precipitation, temperature, available water holding capacity of the soil and others that are representative of the moisture in the system. Some examples of meteorological drought indices are the Palmer Drought Severity Index (PDSI), Palmer Z-Index, the Standardized Precipitation Index (SPI), the Standardized Precipitation and Evapotranspiration Index (SPEI), the Effective Drought Index, and deciles. The rationale for selecting PDSI, SPI and SPEI for evaluation in this thesis is that they are popular indices that use different approaches for characterizing drought conditions. The PDSI, although given a low score in an evaluation performed by Quiring (2009), is a popular drought index especially in the United States. The SPI and SPEI are similar to each other in calculation, but use two different inputs (precipitation versus precipitation and temperature) and can be calculated for any time scale of interest.

2.3 National Drought Monitoring

Bordi and Sutera (2001) summarized different methods for drought monitoring and forecasting at the national scale and concluded that using an ensemble of different methods is the best approach for providing information for drought risk assessment and planning. In the United States, the National Drought Mitigation Center (www.drought.unl.edu) is an organization that helps people and institutions develop and implement measures to reduce societal vulnerability to drought. The National Integrated Drought Information System (www.drought.gov) was established in 2006 to provide information about current drought conditions, forecasting, impacts and planning. A web-based GIS from NOAA provides the information in an interactive format (Brewer and Symonds 2009). State and local agencies can use the above information, supplemented with more localized information, to evaluate and contextualize local drought conditions and determine how to respond. Table 2.1 lists some of the drought monitoring tools available in the U.S. and their spatial resolution. Figure 2.3 shows the state of drought monitoring plans as of 2011 in different states of USA.

Table 2.1. Drought monitoring tools available in the United States

Drought Index	Developed by	Indicators/Inputs	Resolution available
Crop moisture index – MAP	(Palmer, 1965)	Difference in potential and actual evapotranspiration	344 NCDC climate divisions
National Weather Service: Precipitation Analysis- MAP	National Weather Service (http://water.weather.gov/precip/)	Precipitation	4*4 km grid
NLDAS Drought Monitor	(Huang et al. 1996)	Soil moisture	344 NCDC climate divisions
PDSI	(Palmer, 1965)	Precipitation, temperature, available water holding capacity	344 NCDC climate divisions
Daily Gridded SPI	(McKee et al. 1993; McKee et al. 1995)	Precipitation	COOP stations, 0.4 degrees
U.S. Drought Monitor	National Drought Mitigation Center (http://droughtmonitor.unl.edu/)	Multiple drought indices and impact reports	-
Percent of normal precipitation	PRISM group, Oregon state (http://www.prism.oregonstate.edu)	Precipitation, normal precipitation	4*4 km grid

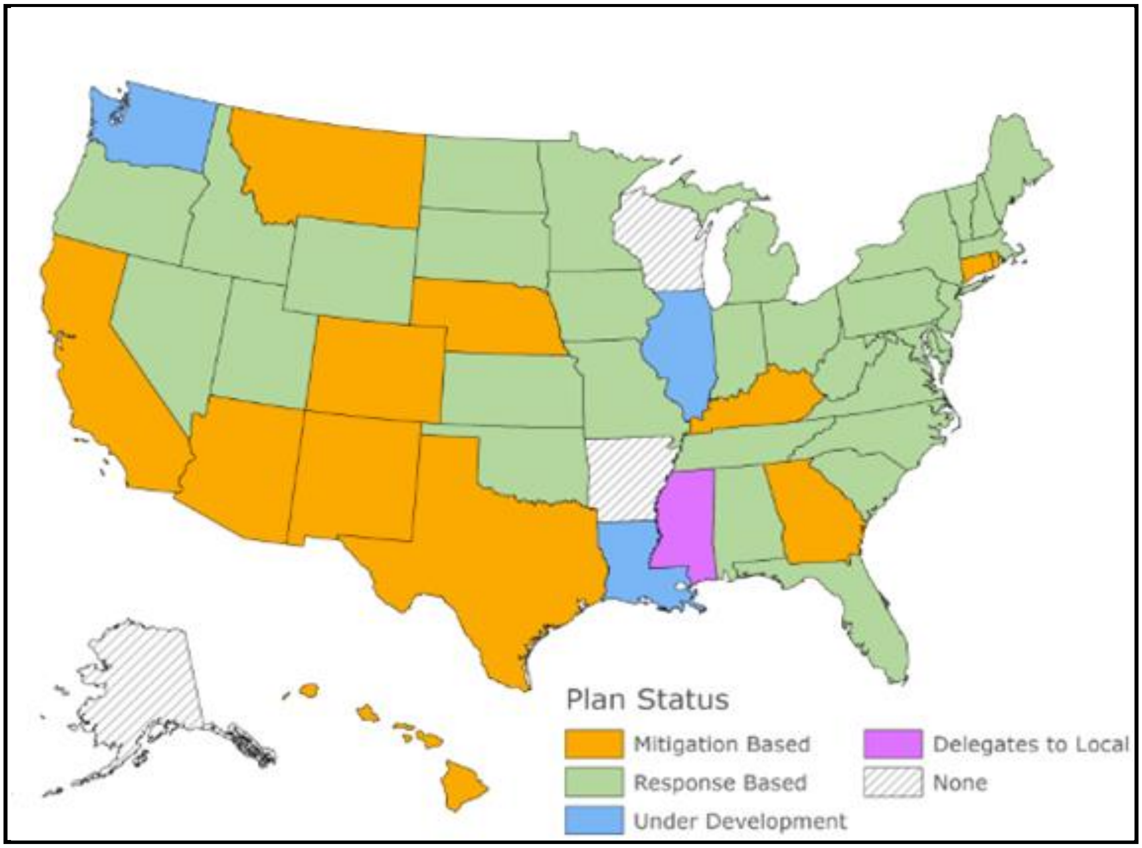

Figure 2.3 Status of state drought plans as of 2011 (National Drought Mitigation Center, 2011)

2.4 Literature Review

The commonly assessed spatial interpolation methods for drought indices are Inverse Distance Weighted, thin plate splines and ordinary kriging (Akhtari et al. 2009; Ali et al. 2011; Carbone et al. 2008). Jin and Heap (2008) analyzed the frequency of use of major interpolation methods in the environmental sciences and found that three most frequently used types of methods were IDW, ordinary kriging and thin plate splines. These three methods follow three different techniques of prediction (Jin and Heap 2008) which are deterministic, geostatistical and mathematical. Numerous studies have been done to assess the influence of interpolation methods on variables such as precipitation and temperature. Since the variable that is being interpolated, the climatic region, and the topography of the study area all can influence the accuracy of the interpolation, this influence needs to be quantified to understand it better.

Carbone et al. (2008) assessed the suitability of IDW, thin plate splines, kriging and Thiessen polygons using cross validation for 316 COOP stations in North and South Carolina for both PDSI and SPI (~12 stations per 10,000 km^2). They concluded that IDW and kriging performed similarly and both outperformed thin plate splines and Thiessen polygons by a significant margin.

Akhtari et al. (2009) compared IDW, ordinary kriging and thin plate splines over the Tehran province of Iran for 43 stations (~22 stations per 10,000 km^2) using the 1-month SPI and Effective Drought Index (EDI). They observed that IDW and kriging outperformed thin plate smoothing splines. Although kriging gave slightly better results, IDW was preferred for its simplicity. Ali et al. (2011) repeated a similar procedure for 27 climatic stations in Boushehr province of Iran (~12 stations per 10,000 km^2) and found similar results. IDW performed slightly better than kriging for SPI and the opposite was true for EDI.

The above three studies compared SPI and/or PDSI for three major types of interpolation methods, but all of the studies were conducted over relatively small areal extents (North and South Carolina, Tehran and Bousher provinces of Iran). A study that spans larger areal extent with variations in climatic regions, topography and station density can help identify the influence of other sources of spatial variability of drought indices.

Kuilenburg et al. (1982) assessed IDW, kriging and thin plate splines for interpolating soil moisture on a small plot of 359 ha in Netherlands (1.5 stations per ha; 1.5 x 10^6 per 10000 km^2) and found similar performances in all methods. This study demonstrates that under ideal conditions (e.g., station density, topography) many interpolation methods give similar results. Goovaerts (2000) suggests that deterministic interpolation methods such as IDW work well with dense networks, whereas geostatistical approaches are better for sparse networks. Dirks et al. (1998) suggests that a dense network is one that has a density of 13 stations over 35 km^2(~3700 stations per 10000 km^2). This density is not typically possible in practice. For example, the average density of COOP network (with sufficient long term data) over contiguous U.S. is ~4.80 stations per 10,000 km^2 and for USHCN the average density is 1.5 stations per 10,000 km^2.

Piazza et al. (2011) analyzed interpolation methods (IDW, ordinary kriging, linear and geographically weighted regression, artificial neural networks) for monthly and annual precipitation data over 247 stations in Sicily, Italy (~96 stations per 10,000 km^2). They observed that ordinary kriging performed better than other univariate methods and the multivariate methods that considered elevation data improved the results (linear regression, geographically weighted regression). The inclusion of elevation is important because Sicily is an island with significant topographical variation.

Vicente-Serrano et al. (2003) assessed IDW, thin plate splines, regresson models, and a number of kriging methods (ordinary, block, universal and co-kriging) for interpolating annual precipitation and temperature in middle Elbro valley in Spain (>200 stations per 10,000 km^2). They compared the interpolated values with independent weather stations and found that the best interpolation methods were different for precipitation and temperature. The best results for precipitation were obtained using geostatistical methods and regression worked better for temperature. When the geostatistical and regression methods incorporated elevation information, they performed better than the methods that did not use elevation.

The above two studies demonstrate the importance of incorporating elevation information when interpolating variables such as precipitation, especially in regions with uneven topography. This is also supported by an interpolation study that examined daily precipitation in the Luohe watershed (~80 stations per 10,000 km^2) where incorporation of elevation improved results (Zhang and Srinivasan 2009).

Although many interpolation methods have been analyzed for common environmental variables at a variety of temporal and spatial scales, there have been relatively few studies comparing interpolation methods for drought indices over a large spatial extent that spans diverse topography and climate regions. The literature review suggests that it is useful to compare deterministic (IDW), geostatistical (kriging) and mathematical (splines) methods and that using variables such as elevation (or variables characterizing spatial complexity) may improve interpolation accuracy.

Chen et al. (2010) is one study that spans a large area. They compared ordinary kriging, IDW, radial basis function, local polynomial and nearest neighbor for daily precipitation values over 753 stations spanning the extent of China (~0.84 stations per 10,000 km^2). The spatial density of stations is significantly higher in the eastern part of the country than the western part and that is reflected in the results. Cross validation suggested that ordinary kriging and IDW (power =2) performed better than all other methods and the difference between them is not substantial. This is an example of study that covers a very large area and has a low density of the stations where IDW works almost as well as kriging.

In the present study, preliminary research was done to compare the three basic methods (IDW, thin plate splines and kriging) and incorporated elevation data into kriging with external drift. Preliminary research demonstrated that thin plate splines are computationally intensive and the method performed significantly worse than ordinary kriging and IDW. Therefore, thin plate splines were not considered further. In addition, in preliminary tests, the accuracy of kriging did not improve when combined with elevation data and therefore this approach was not evaluated further. This study will focus on evaluating two versions of IDW and the optimal method of kriging over the contiguous U.S. to determine the best approach for interpolating meteorological drought indices. The goal is to draw general conclusions about interpolation that can be applied to other variables and other regions and not necessarily to test all spatial interpolation methods.

3. DATA AND METHODS

3.1 United States Historical Climatology Network (USHCN)

The United States Historical Climatology Network (USHCN) version 2 is a high-quality set of 1218 observing stations (Figure 3.1) across the 48 contiguous states that provide daily and monthly records of basic meteorological variables. Daily data include observations of maximum and minimum temperature, rainfall amount, snowfall amount, and snow depth. Monthly data consist of monthly-averaged maximum, minimum, mean temperature and total monthly precipitation (http://cdiac.ornl.gov/epubs/ndp/ushcn/background.html). Most of these stations are U.S. Cooperative Observing Network stations that are generally in rural locations, while some are National Weather Service First-Order stations that are commonly located at airports. The monthly data required for calculations of drought indices were downloaded from USHCN version 2 database and used for calculating drought indices for every station. The network has a duration of record from 1895-present (Menne et al. 2009). The average station density is 1.5 stations per 10,000 km^2. The USHCN stations are evaluated for data quality and subjected to time of observation bias adjustments and homogeneity testing (Menne and Williams 2009).

3.2 National Weather Service Co-operative Observation Network (COOP)

The co-operative observation (COOP) network consists of volunteer observers that span the continental United States with over 11,000 observers taking measurements for daily variables. The monthly data from COOP network was downloaded from the

National Climatic Data Center's website (http://www.ncdc.noaa.gov/oa/ncdc.html). The guidelines for taking measurements were established by the National Weather Service (NWS 2010). Since all of the stations do not have the requisite length of record for calculating drought indices, the stations were filtered and only those with >30 years of data were used in this study. The data was filtered based on the flags provided for every observation. Observations with missing values were excluded. The estimated and adjusted values were included in the calculation. The data available from National Climatic Data Center (NCDC) consisted of >20,000 present and past stations with many temporal breaks and uneven record lengths. These stations were distilled down to ~4,000 suitable stations for each month (Figure 3.2) for calculation of drought indices. The average station density is ~5.80 stations per 10,000 km^2.

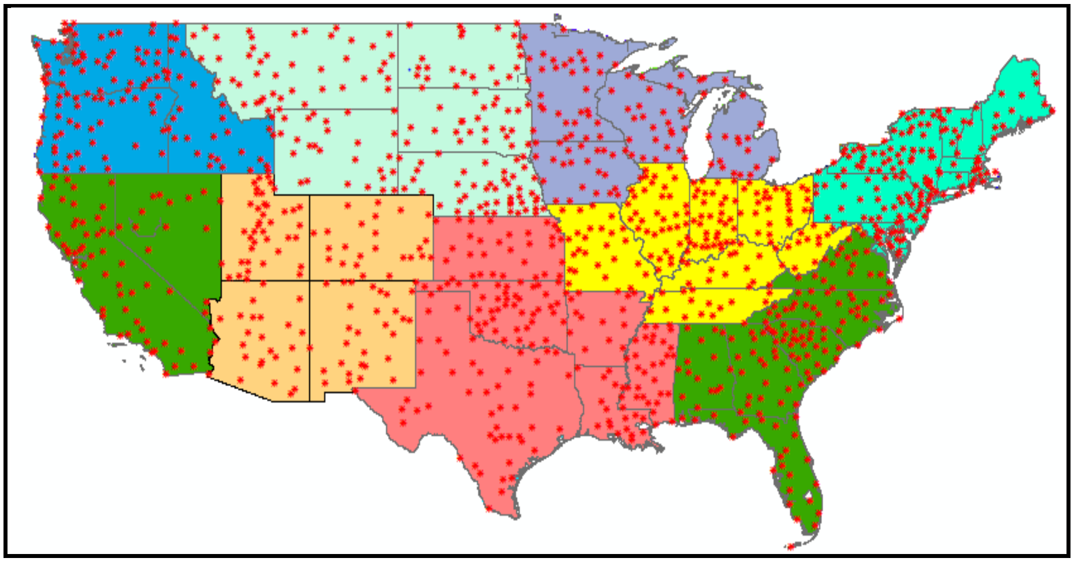

Figure 3.1 USHCN stations in the contiguous U.S. and the 9 climatic regions (~1200 stations); (USHCN 2011)

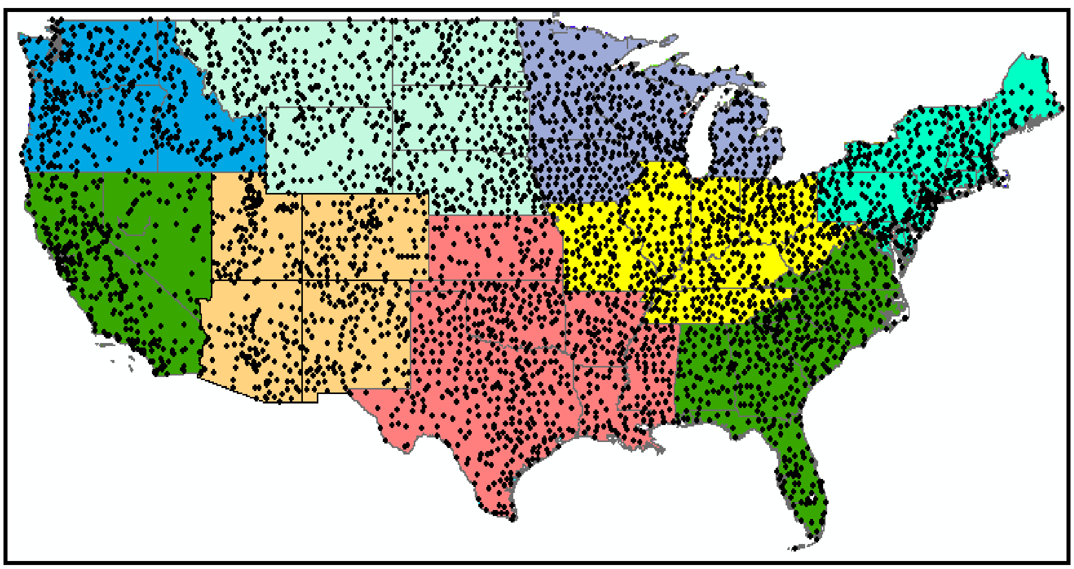

Figure 3.2 NWS COOP filtered stations in the contiguous U.S. and the 9 climatic regions (~4000 stations); (NCDC 2011)

Temperature and precipitation data from USHCN and COOP were used to calculate the drought indices. The SPI is based solely on precipitation data, while the SPEI and PDSI are based on temperature and precipitation data. The PDSI also requires the available water holding capacity of the soil at each station. These data (available water holding capacity) were obtained from a dataset called the Global Soil Texture and Derived Water Holding Capacities (Webb et al. 2000) that has a 1 degree latitude/longitude resolution.

3.3 Methods

The following section summarizes the calculation of moisture (drought) indices, spatial interpolation methods, statistical comparisons and the cross validation technique. The COOP data were filtered to remove stations with incomplete and missing data. Only months with simultaneous availability of precipitation and temperature data are considered so as to enable comparison between all indices. The criteria used for selecting COOP stations is that every station with at least 30 years of historical record for all months are selected. The higher quality of USHCN station data meant that much less filtering was needed. The data obtained from USHCN and NWS COOP were used to calculate drought index values for all months and years available. These drought index values (in selected years 2001 to 2010 excluding 2004 and 2008) were subjected to cross validation to evaluate the accuracy of each interpolation method. The mean absolute errors for stations were calculated and stations with at least 6 years of mean absolute errors were used to calculate average mean absolute error at a single station. Separate evaluations were done for each dataset, month, and moisture index. The average values for all the years in a certain location are considered for some comparisons like evaluation of spatial variation of errors across the extent of USA.

Paired t-tests are performed to compare the performance of each pair of spatial interpolation methods for each of the different cases, the comparison of interpolation errors between indices and between months. To account for the effect of spatial autocorrelation in comparing absolute errors the paired t-tests are performed using n/2 degrees of freedom instead of the typical n-1 degrees of freedom. An example of how this influences the results is shown at the end of this section. The examination of spatial variation of error is done using mean error values for all stations based on 2001 to 2010. The absolute cross validation error is used for comparing interpolation methods across months and climatic regions. The sample size for every individual paired t-test is restricted to a particular month and climatic region and the output of the test is stored as a categorical variable (e.g., for the case kriging performs significantly better than IDW 2.5). The degrees of freedom are n/2 for each instance. Multiple tests are performed for the comparisons under consideration. The results of these multiple tests are categorized to make deductions. Multiple stations distributed over a climatic region and number of years considered give a large sample size. The paired t-tests work for different comparisons because at the most basic level the absolute errors being compared have a one to one correspondence at the station level and a number of differences are checked for normal distribution. While comparing absolute errors of individual drought indices using paired t-tests the PDSI values were normalized by the standard deviation of PDSI for every instance of comparison. These normalized values are used to enable comparison between PDSI and the other two indices.

3.4 Drought Indices

3.4.1 Palmer Drought Severity Index (PDSI)

The PDSI is one of the oldest and most widely used drought indices (Palmer 1965). It requires precipitation, temperature and available water holding capacity of the soil for calculation.

The moisture anomaly index (Z-index) is part of the PDSI and it is a measure of how monthly moisture levels compare to expected values calculated based on at least 30 years of data. The expected moisture level is determined based on a water balance equation. The moisture anomaly for the month is standardized for the month and location using a weighting factor.

$$z_{\mathrm{i}} = d_i k_i$$

$$k_i = \left(\frac{17.67}{\sum D_i k'}\right) k'$$

d_i – difference between existing precipitation and precipitation appropriate for existing climatic conditions, an indicator for water deficiency

k_i - weighting factor calculated using equation above

Di - average of absolute values of di

k' - depends on average supply and demand calculated using a different formula

17.67 was an empirical co-efficient initially suggested by Palmer for the original Palmer Z-index that is modified in the formula for calculating the self-calibrated version of the PDSI. The PDSI is a combination of Z-index for the current month and PDSI for the previous month.

$$x_i = \left(\frac{z_i}{3}\right) + 0.897x_{i-1}$$

The Z-index can vary greatly from month to month, whereas PDSI fluctuates more slowly because it is influenced by PDSI values in previous months. Guttman et al. (1992) demonstrated that the PDSI was not comparable spatially in terms of identifying rare events. Wells et al. (2004) introduced a self-calibrating PDSI which replaced the empirical constants by dynamically calculating values for each location. The evaluation of the self-calibrated PDSI showed it to be more spatially comparable than the original PDSI. In this study the self-calibrated PDSI was used. The inherent time-scale of PDSI is about 9 months, which means that the PDSI represents moisture conditions for this duration.

Software published by the National Drought Mitigation Center (www.greenleaf.unl.edu) was used for calculating the self-calibrated PDSI. A batch process was set up using python scripts. PDSI values were not calculated for months in which precipitation or temperature data were absent (Wells 2004; Greenleaf 2011). This includes all months affected by the missing values in addition to the months with missing values themselves.

3.4.2 Standardized Precipitation Index

The Standardized Precipitation Index was developed by McKee et al. (1993) and is supposed to overcome the shortcomings of PDSI (e.g., cannot be used for multiple time scales, original PDSI could not be compared spatially). SPI uses only precipitation data for its calculation and fits a mathematical function to the historical precipitation data. The SPI is designed to be spatially and temporally comparable because the values are standardized by the fitting function. Different probability distributions give slightly different values and for the sake of spatial comparison the same function is used at all the locations. The SPI values are standardized such that the mean is zero and negative and positive values indicate drier than normal and wetter than normal conditions, respectively. The commonly used probability density functions for calculation of SPI are log-logistic, Gamma and Pearson Type 3. One advantage of SPI is that it can be calculated for any time period of interest (i.e., it is multiscalar) provided sufficient data are available. After fitting the historical precipitation record with a probability density function, the record is transformed using an inverse normal function (Guttman 1999). Table 3.1 shows the SPI values and associated moisture conditions defined by McKee et al. (1993).

Table 3.1 SPI classification, McKee et al. (1993)

SPI values	Probability	Moisture conditions
< -2	2.30%	Extremely dry
> -1.5 and < -2.0	4.40%	Very dry
> -1.0 and < -1.5	9.20%	Moderately dry
> -1.0 and < 1.0	68.20%	Near normal
> 1.0 and < 1.5	9.20%	Moderately wet
> 1.5 and < 2.0	4.40%	Very wet
> 2.0	2.30%	Extremely wet

The SPI for 1-, 6-, 9- and 12-month time-scales were evaluated in this study. The Gamma distribution used for the SPI is given by Thom (1966) as:

$$g(x) = \frac{1}{\beta^{\alpha}\gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$$

β is a scale paramter , α is a shape parameter , $\gamma(\alpha)$ is an ordinary gamma function of α.

Probabilities are given by the distribution function as

$$g(x) = \int_0^x g(t)dt$$

A mixed distribution function (Thom 1951) is used by SPI as the precipitation distribution may contain zeroes as given by where *q* is the probability of a zero, and is estimated by *m/n*, in which *m* is the number of zeros in a precipitation time series *n*.

$$H(x) = q + (1 - q)G(x)$$

SPI is finally calculated using a rational approximation approach (Hastings 1955)

$$SPI = -(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3})$$

for $0 < H(x) \leq 0.5$

$$SPI = \left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right)$$

for $0.5 < H(x) \leq 1.0$

$c0 = 2.515517$
$c1 = 0.802853$
$c2 = 0.010328$
$d1 = 1.432788$
$d2 = 0.189269$
$d3 = 0.001308$

The R package SPEI (Begueria and Vicente-Serrano 2011) was used to calculate the SPI. The software calculates the SPI for different durations (from 1 to 12 months) using the gamma distribution. No SPI values were calculated for months with missing precipitation data. All SPI months that included missing months were set to missing and not considered in the analysis.

3.4.3 Standardized Precipitation and Evapotranspiration Index

Vicente-Serrano et al. (2010) proposed a new drought index called the Standardized Precipitation and Evapotranspiration Index (SPEI). The SPEI is based on temperature and precipitation data. This index accounts for water demand due to evapotranspiration and according to Vicente-Serrano et al. (2010), it is comparable to the self-calibrating PDSI. The advantage of SPEI over PDSI is that it can be calculated over multiple time periods like SPI and hence can be used to understand drought severity over different time scales. The calculation of SPEI is similar to SPI except that the function is fit to precipitation minus potential evapotranspiration (P-PET) values. The PET value can be calculated using different equations that link it to the temperature value. The Thornthwaite (1948) equation was used to estimate PET in this study.

$$PET = 16k(\frac{10T}{i})^m$$

In the above equation T is monthly temperature in degree Celsius

i is heat index derived from 12 monthly index values calculated as a sum of 12 monthly index values *i*, which is calculated as given in the equation below

$$i = (\frac{T}{5})^{1.514}$$

m is a coefficient depending on *i*, and k is a correction coefficient computed as a function of the latitude and month.

The difference between precipitation and potential evapotranspiration provides a measure of water surplus or deficit for the month and this is compared over time and standardized to get the value of SPEI.

$$d_i = P_i - PET_i$$

d_i - a difference of precipitation and potential evapotranspiration for month i.

The process for SPEI calculation skipped missing values and SPEI is not calculated for months in which no data are available. This includes all SPI periods affected by the missing months. The Gamma distribution was used for calculating the

SPEI using R package SPEI (Begueria and Vicente-Serrano 2011). The calculation of SPEI is analogous to SPI, but since the difference between precipitation and potential evapotranspiration can be either positive or negative a 3-parameter gamma distribution (which can take both positive and negative values) is used to calculate the SPEI.

3.5 *Spatial Interpolation Methods*

This study focuses on the interpolation of moisture (drought) indices that are calculated using temperature and precipitation. Although there have been numerous studies that have focused on interpolation methods for temperature and precipitation, they may not be directly applicable to moisture indices since the spatial variability of these indices is different. As an example, spatial interpolation is more accurate for temperature data as compared to precipitation data because there are fewer factors that affect its variation (Vicente-Serrano et al. 2003). Jin and Heap (2008) evaluated the frequency of use of a number of different spatial interpolation methods used in the environmental sciences and the results are summarized in the Figure 3.3. They found that the most commonly used spatial interpolation methods are inverse distance weighted (IDW), inverse distance squared (IDS), ordinary kriging (OK) and thin plate splines (TPS). The IDW, OK and TPS methods were initially selected for the study. Preliminary research showed that TPS performed far worse than both IDW and OK methods and that it is computationally demanding. Therefore, TPS was not considered further. Preliminary research also compared OK to other variants of kriging with external drift. As the latter did not produce significant improvement over OK, this thesis will focus on evaluating two variants of IDW (power parameters 2 and 2.5) and a version of OK that uses optimal fitting for the semivariograms.

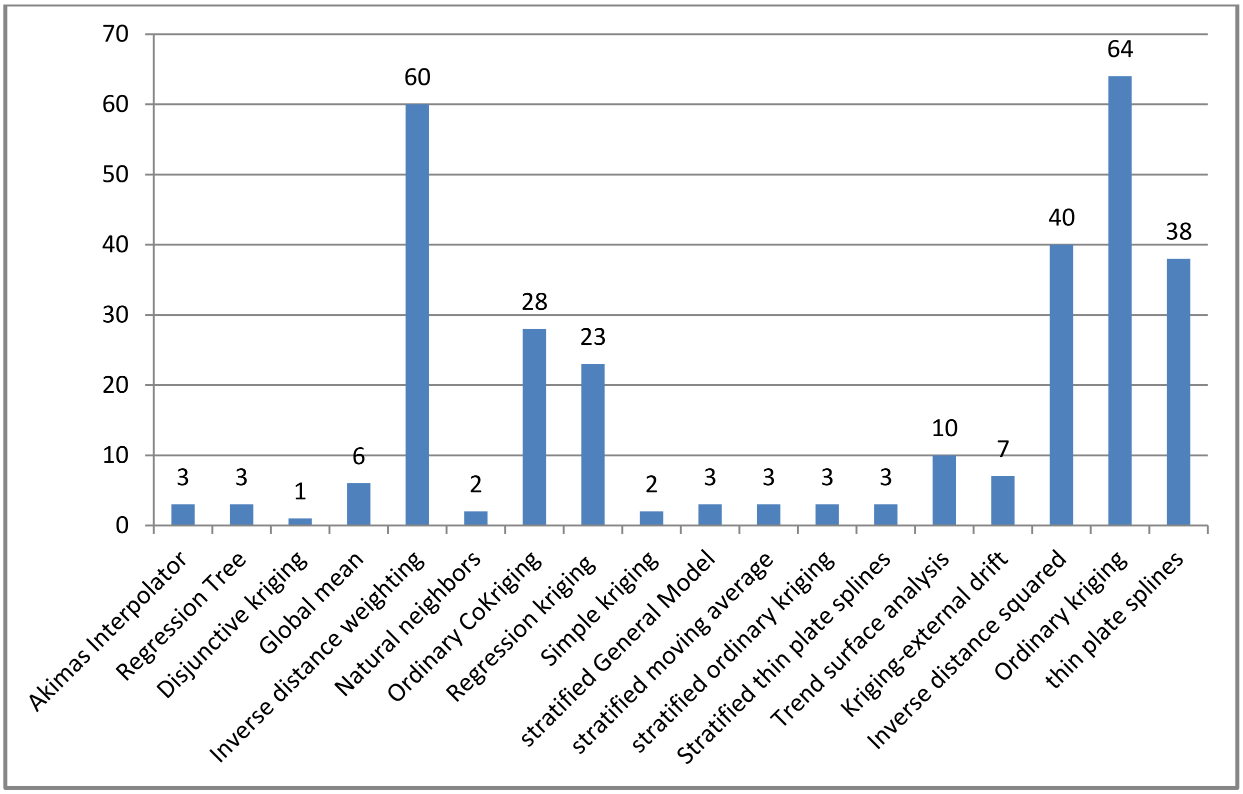

Figure 3.3 Frequency of spatial interpolation methods used in the environmental sciences (Jin and Heap 2008)

The general formula for spatial interpolation is:

$$z(s_o) = \sum_{i=1}^{n} \lambda_i \, z(s_i)$$

Where:

$z(s_i)$ = measured value at the i_{th} location

λ_i = weight for the measured value at the i_{th} location

s_o = prediction location

n = number of measured values

$z(s_o)$ = value at prediction location.

3.5.1 Inverse Distance Weighting (IDW) Method

Inverse distance weighting estimates the value at an unsampled location based on a specified number of surrounding points or a number of points within a certain radius. This is a deterministic method and no estimate concerning the accuracy of prediction is available. Weights are assigned to each of these points as an inverse function of their distance from this point. An additional parameter called the power parameter controls the relative weight to be given to the distance variable. A number of iterations are generally needed before deciding on factors such as number of surrounding points to be used, maximum or minimum radius, and the power parameter. Cross validation is one method that can be used to determine the most appropriate parameters for IDW. The coefficient for IDW method is defined as

$$\lambda_i = (1/d_i^p)/(\sum 1/d_i^p)$$

In above equation λ_i is the coefficient value to be used for a particular point at a distance d_i from the point whose value is to be interpolated. These coefficients are calculated for all points within a certain radius or a specified number of points (and summation is done accordingly). The maximum number of points used in this method was 15 for COOP (10 for USHCN) and with a radius limitation of 150 km for COOP and 200 km for USHCN. Preliminary analyses demonstrated good performance for IDW using power parameters ranging from 2 to 2.5. Therefore, these two power parameters were used in the final analysis. Note that IDW with power parameter 2 is called as inverse distance squared method. The preliminary analyses demonstrated that performance decreased when higher or lower power parameters were used.

3.5.2 Kriging

Kriging is the generic name for a family of generalized least squares regression algorithms that originated with the pioneering work of Daniel Krige (Krige 1951). Kriging requires exploratory analysis of the data prior to interpolation. In ordinary kriging the weight depends on a model fitted to the measured points, the distance to the prediction location and the spatial relationship amongst the measured values near the prediction location.

Kriging is based on the concept of spatial autocorrelation and it assumes that the observations are an outcome of some spatial correlation function which can be estimated from the available data. Kriging assumes that the value at a location is a realization of a process which can be modeled by a semivariogram. A semivariogram models the semivariance between all pairs of points against the distance between the pairs of points as shown in Figure 3.4.

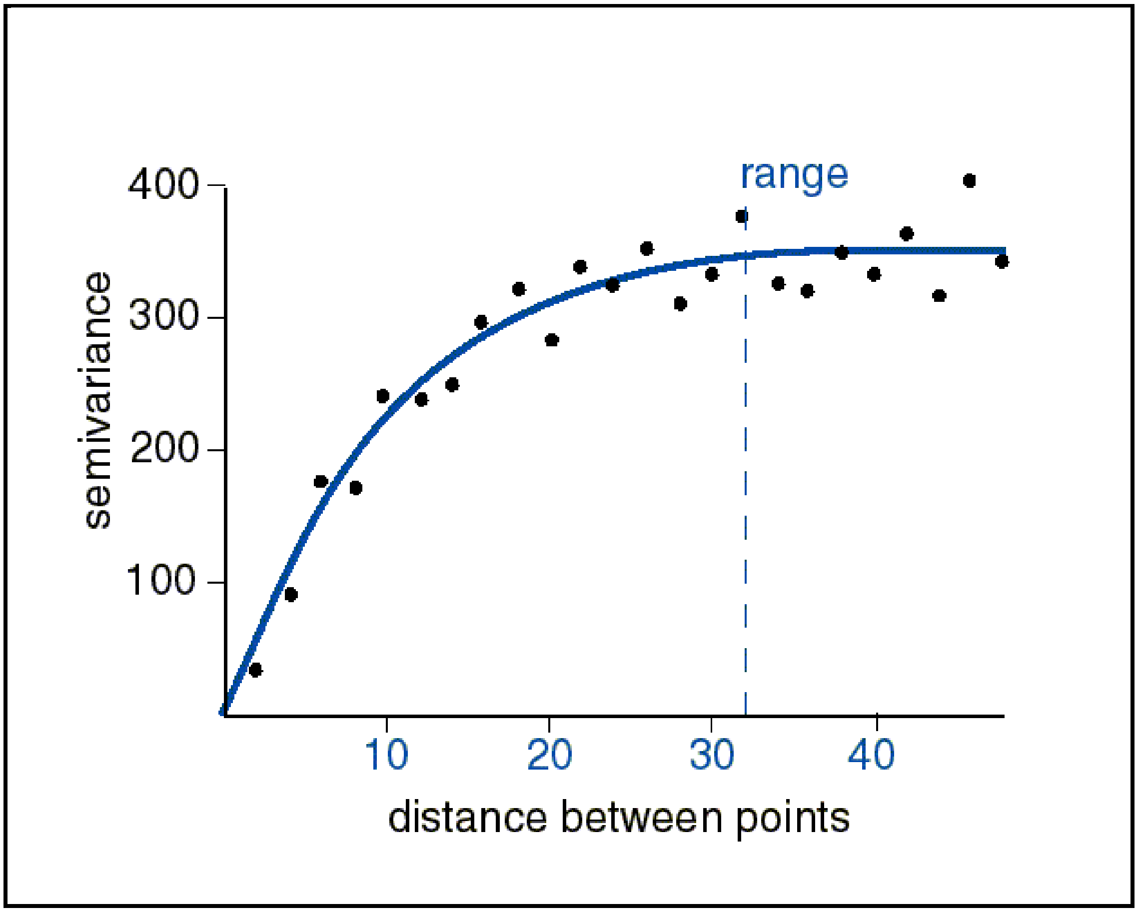

Figure 3.4 Example of a semivariogram (Rossiter 2011).

The empirical semivariogram (i.e., variogram based on data) is calculated as:

$$\gamma(\hbar) = \frac{1}{2m(\hbar)} \sum_{i=1}^{m(\hbar)} [z(x) - \mathrm{z}(\mathrm{x} + \mathrm{h}_i)]^2$$

Where:

m (h) is the number of point pairs separated by some range

Point pairs are indexed by i, and the notation $x+h_i$ means the tail of a point pair is separated from the head by a separation vector h_i. This function is modeled with an appropriate theoretical variogram.

For COOP stations the nearest 500 stations are used for modeling the variogram (200 for USHCN) for every station under consideration. The functions used for fitting the variogram are Gaussian, Spherical and exponential model using least squares fitting by R library Automap (Hiemstra et al. 2008). Although many different semivariograms are available, in this study it is not possible to perform exploratory data analysis and determine the most appropriate semivariogram for each instance. Therefore, the theoretical semivariogram fitting was achieved using least squares fitting based on library automap that iterated over three models and fitted the best model. This method provides an objective approach for fitting the semivariogram. Kriging with external drift using elevation, precipitation and temperature data was compared with OK in preliminary research, but as there was no overall improvement in accuracy using this approach, optimal ordinary kriging was used in this study.

3.6 Cross Validation Method

Cross validation is a technique used to evaluate the accuracy of a predictive model (Isaaks and Srivastava 1989). In this case, the spatial interpolation method "predicts" the value of a drought index at unsampled locations based on values at neighboring stations. Typically it is not possible to know how close the predicted value at the unsampled location is to the true value. The cross validation technique used in this study is a leave-one out cross-validation. In this approach one climatic station is removed and the value at that location of the station is interpolated (predicted) using the remaining stations, this value is called the predicted value. This method is valid because removal of one point from a very large number of points will not have a significant effect on overall prediction. The difference between actual value at a particular location and the predicted value is the residual error and its absolute value is called the absolute error. The absolute error and normalized absolute error (calculated over a group of absolute errors (e.g., all stations within a climatic region)) are measures of the predictive accuracy for that instance. These values are used as performance metrics to evaluate the accuracy of interpolation methods. The cross-validation procedure was implemented using code written in 'R'.

3.7 Overview of Methods

Python was used for batch programming and calculating PDSI. The statistical package “R” was used for spatial interpolation and calculating values of SPI and SPEI. Data conversions were achieved using Excel. Figure 3.5 provides an overview of the approach that was used to evaluation interpolation methods in this study. The accuracy of IDW 2, IDW 2.5 and optimal ordinary kriging are assessed using a leave-one-out cross validation. The results of the interpolation accuracy evaluation are summarized for 9 climatic regions, 3 months (January, July and October) based on data from 2001-2010 (excluding years 2004 and 2008). The SPI and SPEI results are compared individually for different scales (1-, 6-, 9-, and 12-months) under consideration. This is done for USHCN and COOP datasets independently.

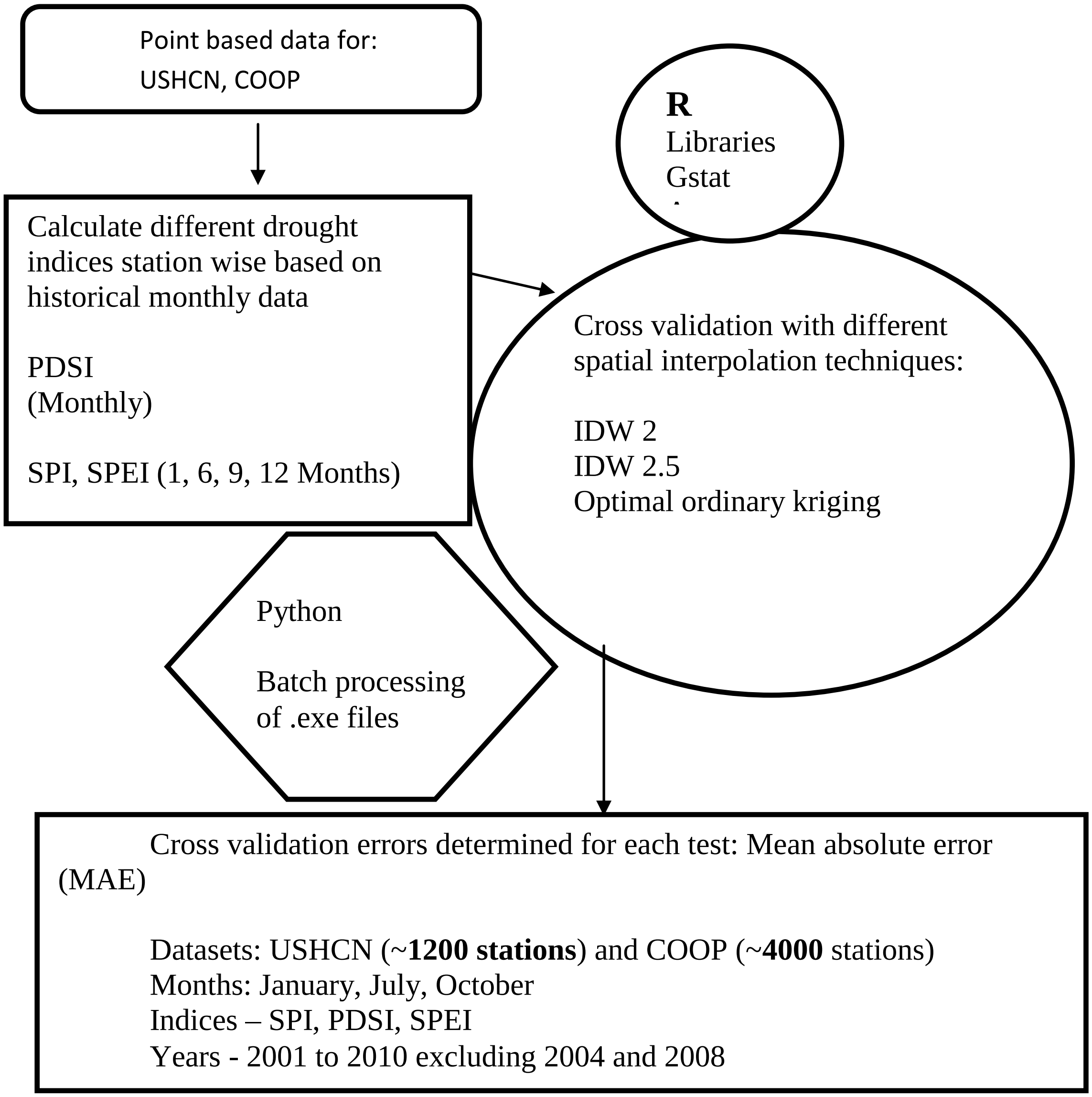

Figure 3.5 Overview of methods

1

3.8 Paired t-test Modification

To account for autocorrelation in the absolute error values at nearby stations, n/2 degrees of freedom have been used instead of n - 1. This changes the critical value required to reject the null hypothesis and gives a more conservative result. However as the sample size in each case is large, the effect of using n/2 degrees of freedom is minimal. A sample comparison is shown below.

Comparison between normalized values of PDSI and 9-month SPEI for Northwest climatic region for the month of October.

Sample size = 1471

test statistic t = -2.454

critical value for n-1 degrees of freedom (1470) = 1.646

critical value for n/2 degrees of freedom (735) = 1.650

The null hypothesis (that the difference is 0) is rejected in both cases.

3.9 Climatic Regions

Figure 3.6 shows the different climatic regions of the United States (administrative) and these are used to compare aggregated results spatially. These are the climatic regions established by National Climatic Data Center (NCDC) and they are defined in Table 3.1. Table 3.2 shows the total area, number of stations and station density for each region. Figure 3.7 shows the variation of mean annual precipitation for each region using values from USHCN dataset.

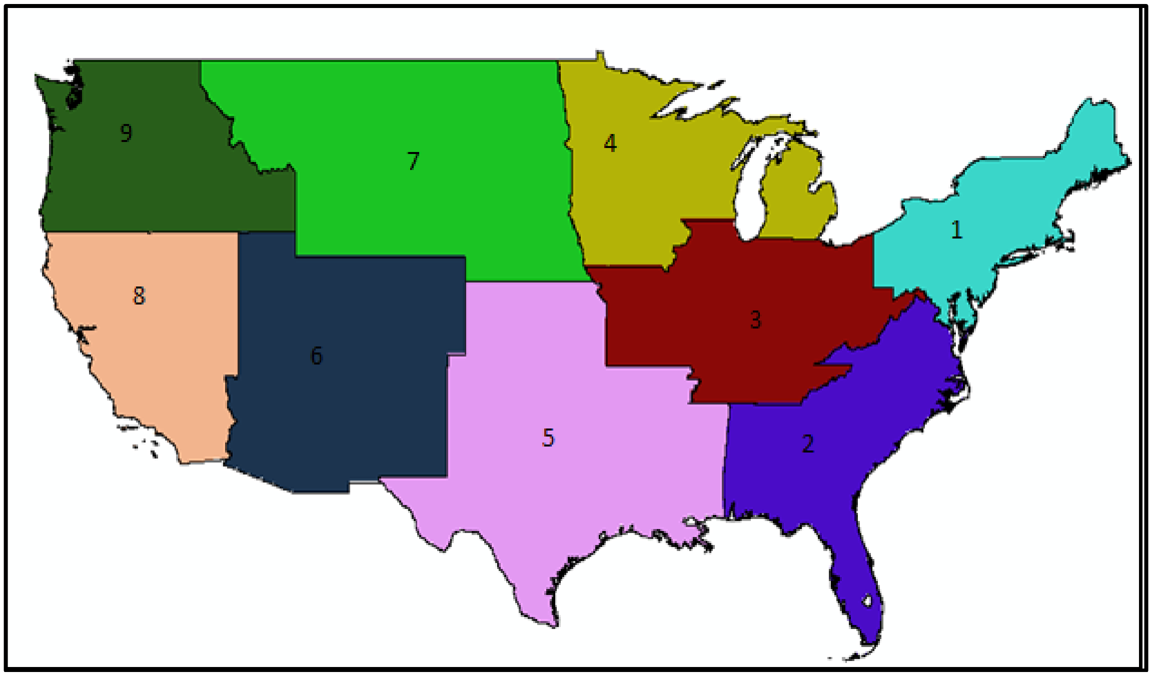

Figure 3.6 Climatic regions of the contiguous United States (NCDC 2011)

Table 3.2 Legend: Climatic regions of the contiguous United States

No.	**Region**	**States**
1	NorthEast	Connecticut, Delaware, Maine, Maryland, New Hampshire, New Jersey, New York, Pennsylvania, Rhode island, Vermont
2	SouthEast	Alabama, Florida, Georgia, North Carolina, South Carolina, Virgina
3	Central	Kentucky, Illinois, Indiana, Missouri, Ohio, Tennesse, West Virginia
4	EastNorthCentral	Iowa, Michigan, Minnesota, Wisconsin
5	South	Arkansas, Louisiana, Kansas, Mississippi, Oklahoma, Texas
6	SouthWest	Arizona, Colorado, New Mexico, Utah
7	WestNorthCentral	Montana, Nebraska, North Dakota, South Dakota, Wyoming
8	West	California, Nevada
9	NorthWest	Idaho, Oregon, Washington

Table 3.3 Number of stations per climatic region

Region	Area (10,000 km^2)	USHCN: Number of stations	USHCN: Station density per 10,000 km^2	COOP: Number of stations	COOP: Station density per 10,000 km^2
1	45.06	135	3.00	261	5.79
2	72.79	121	1.66	382	5.25
3	79.33	164	2.07	512	6.45
4	63.87	96	1.50	385	6.03
5	143.70	184	1.28	658	4.58
6	109.00	118	1.08	415	3.81
7	120.28	166	1.38	543	4.51
8	68.84	60	0.87	225	3.27
9	65.53	103	1.57	299	4.56

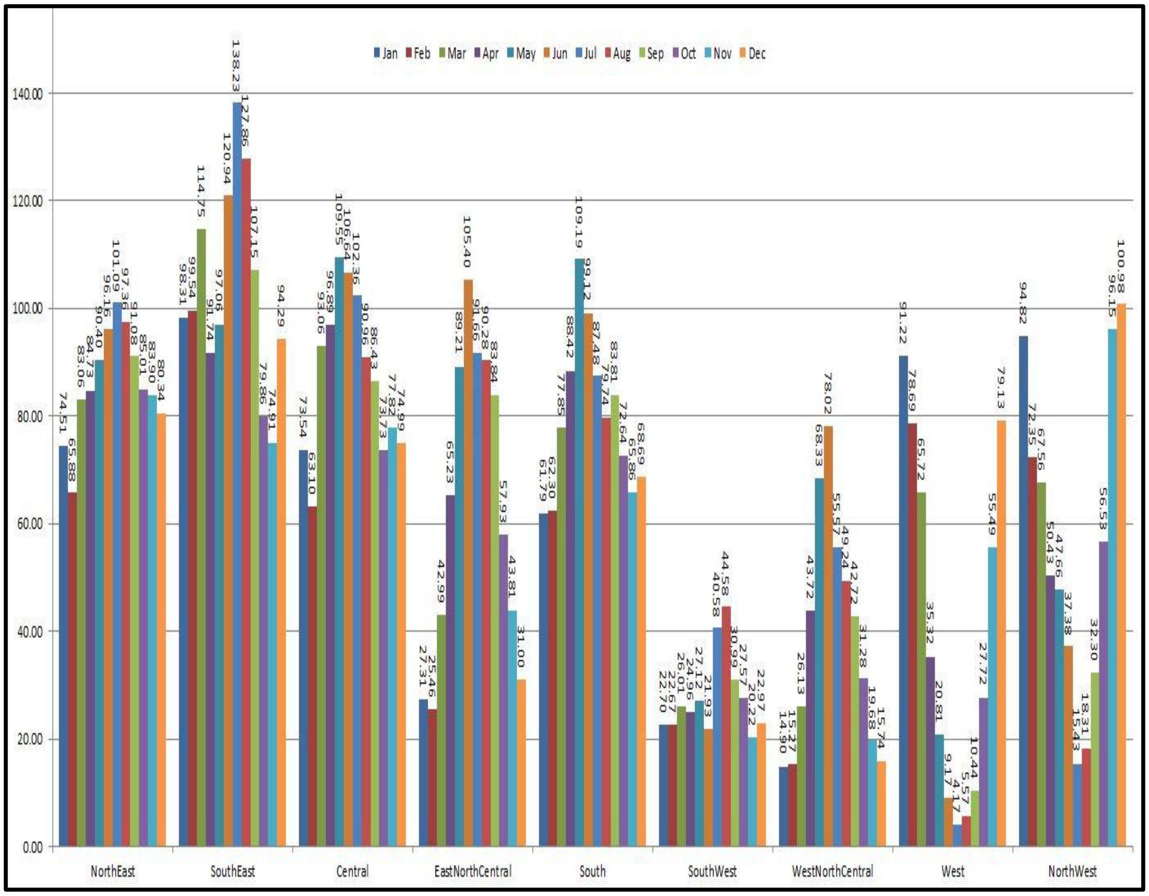

Figure 3.7 Mean monthly precipitation (mm) in 9 climatic regions (NCDC 2011)

4. RESULTS

4.1. Comparison of Interpolation Methods

4.1.1. 1-month SPI

The descriptions below refer to Figures 4.1 and 4.2 that show the mean absolute error (MAE) for 1-month SPI for the 9 climatic regions in the contiguous United States. These errors are calculated for COOP (hereafter denoted by C) and USHCN (hereafter denoted by U) networks. The results are explained independently for each climatic region. The comparisons between months or station density are done using cross validation errors for kriging method.

NorthEast

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.35, U=0.39) followed by IDW 2.5 (MAE: C=0.37, U=0.41) and IDW 2 (MAE: C=0.39, U=0.42) and this can be seen for most of the months (Figure 4.1 and 4.2). The maximum errors occurred in July and August (MAE: C=0.47, U=0.52) and the minimum in October and November (MAE: C=0.28, U= 0.32). Figure 3.7 shows that the highest average precipitation over the NorthEast region occurs in the months of June to August (>100 mm) and lowest from December to February (<80 mm). There is relatively little seasonal variation in precipitation in this region. This region has the highest density of USHCN stations (3.00 per 10,000 km^2) and a relatively high density of COOP stations (5.80 per 10,000 km^2) as compared to the other regions.

The difference between extreme errors (maximum and minimum) are:

seasonality (MAE: C=0.22, U=0.23), interpolation method (MAE: C=0.059, U=0.049) and density of stations (MAE: 0.069). Precipitation climatology is the most significant factors that influences intra-annual variations in accuracy. The highest errors occur in months with the most precipitation (July and August) and the lowest errors occur in months with lower precipitation and more uniform precipitation distribution (October and November). A significant portion of the winter precipitation in this region comes from storms called nor'easters that produce lot of snowfall/rain over a large region in a short amount of time (Rohli and Vega 2011). During the warm season, precipitation is generally from mesoscale convective systems (Murray and Colle 2010) and the remnants of tropical cyclone from south and southeast (Deluca et al. 2002). As a result, interpolation errors are generally higher during the warm season because of the different mechanisms that produce more spatially heterogeneous patterns of precipitation. The values show that variations in accuracy due to the effect of interpolation methods and density of stations are relatively minor in comparison.

SouthEast

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.39, U=0.43) followed by IDW 2.5 (MAE: C=0.40, U=0.45) and IDW 2 (MAE: C=0.44, U=0.49) as observed for most combinations in Figures 4.1 and 4.2. The highest errors occur in July and August (MAE: C=0.56, U=0.61) and the lowest in October and November (MAE: C=0.30, U=0.34). Figure 3.7 shows that the highest average precipitation over Southeast region occurs in months of June to August (>120 mm) and lowest in October and November (<80 mm). This region has a fairly high density of

COOP stations (5.25 per 10,000 km^2) and medium density for USHCN stations (1.67 per 10,000 km^2) as compared to other climatic regions.

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.26, U=0.27), interpolation method (MAE: C=0.098, U=0.09) and density of stations (MAE: 0.059). Precipitation climatology is again clearly the most important driver of variations of accuracy with the errors being highest in the months with the highest precipitation (July and August) as compared to winter months when precipitation is lower. Soule (1998) states that convective storm activity in the form of late afternoon thunderstorms supply most of precipitation for southeast in summer. Larson et al.(2005) mentions that upto ~20% of precipitation in summer along the Gulf of Mexico coast comes from landfalling tropical cyclones. Maximum convective activity occurs in the central part of Florida due to convergence of air masses from Gulf of Mexico and Atlantic Ocean (Lydolph 1985). This gives higher errors in this region and can also be seen in the error maps produced in Section 4.4. Although the density of stations for COOP is more than three times that of USHCN, the improvement in accuracy is marginal. Kriging gives a fair amount of improvement over IDW for this instance.

Central

Kriging gave the best performance for 1-month SPI for all months (MAE: C=0.34, U=0.39) followed by IDW 2.5 (MAE: C=0.36, U=0.41) and IDW 2 (MAE: C=0.41, U=0.46) and this can be seen for all combinations in Figure 4.1 and 4.2. The maximum errors occurred in July and August (MAE: C=0.48, U=0.52) and the minimum in October and November (MAE: C=0.25, U= 0.27). Figure 3.7 shows that the highest average precipitation over Central region occurs in months of May to August (>100 mm) and lowest from October to February (<75 mm).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.23, U=0.25), interpolation method (MAE: C=0.091, U=0.097) and density of stations (MAE: 0.066). Precipitation climatology is again the main driver of accuracy with highest errors in late summer when precipitation is high and lowest errors in October and November coinciding with lower precipitations. An exception is the month of May, which has the highest precipitation but relatively lower errors. Villarini et al. (2011) states that extreme rainfall events in the midwest occurs most frequently in the May-August period and this relates well with the influence on spatial accuracy.

EastNorthCentral

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.35, U=0.43) followed by IDW 2.5 (MAE: C=0.38, U=0.46) and IDW 2 (MAE: C=0.42, U=0.50) and this can be seen for all combinations in Figure 4.1 and 4.2. The highest errors occurred in July and August (MAE: C=0.44, U=0.53) and the lowest in October and November (MAE: C=0.25, U=0.32). Figure 3.7 shows that the highest average precipitation over EastNorthCentral region occurs in months of June to August (~100 mm) and lowest from December to February (<30 mm). The precipitation varies greatly from season to season in this region.

The difference between extreme errors (maximum and minimum) are:

seasonality (MAE: C=0.20, U=0.22), interpolation method (MAE: C=0.105, U=0.112) and density of stations (MAE: 0.107). Precipitation climatology is an important driver of errors but the overall variation of errors seasonally is lesser than previous cases. A substantial portion of precipitation in midwest and great plains in this period occurs from mesoscale convective precipitation systems (Tollerud and Collander 1993; Maddox et al. 1980). Ashley et al. (2003) shows that these occurrences are highest for this region in the months of June and July which coincides with lower interpolation accuracy. Both interpolation methods and station density have a larger effect on accuracy than other regions. The COOP network has a density almost four times the USHCN network in this region and this is reflected in the difference in accuracy between the two networks.

South

Kriging gave the lowest errors for 1-month SPI for all months (MAE: C=0.36, U=0.41) followed by IDW 2.5 (MAE: C=0.38, U=0.44) and IDW 2 (MAE: C=0.43, U=0.49) and this can be seen for all combinations in Figures 4.1 and 4.2. The maximum errors occurred in July and August (MAE: C=0.48, U=0.56) and the minimum in October (C=0.27) and November, (C=0.33). The errors are low from October through March in South. Figure 3.7 shows that the highest average precipitation over South region occurs in months of April to July (>85 mm) and lowest from November to February (<70 mm).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.20, U=0.23), interpolation method (MAE: C=0.109, U=0.124) and density of stations (MAE: 0.085). Precipitation climatology has the most significant effect on errors and the highest and lowest errors clearly correspond to months with higher and lower precipitation amounts. An exception is the month of May. This region covers a large area which is the southern part of the Great Plains and its climatology is influenced by proximity to Gulf of Mexico. Louisiana, Mississippi and Arkansas have significantly higher precipitation than the remaining states where an east-west gradient exists for most of the months with Soule (1998) stating that precipitation is maximized along the Gulf of Mexico. Ashley et al. (2003) notes that about 7-10% of precipitation of warm season (May to September) for this region occurs from mesoscale convective systems which results in higher errors. The effect of interpolation methods is more significant than the density of stations (although station density for COOP is more than three times USHCN in this region).

SouthWest

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.39, U=0.43) followed by IDW 2.5 (MAE: C=0.41, U=0.45) and IDW 2 (MAE: C=0.44, U=0.47) and this can be seen for all combinations in Figures 4.1 and 4.2. The maximum errors occurred in July and August (MAE: C=0.57, U=0.59) and the minimum in October and November (MAE: C=0.37, U=0.40) and the variation across seasonality is very low except for the extreme values. Figure 3.7 shows that the highest average precipitation over Southwest region occurs in months of July and August (>40 mm) and is uniform in the remaining months. Precipitation in this region is lower than all other climatic regions, as is the intra-annual variation of precipitation (Guirguis and Avissar 2008).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.24, U=0.23), interpolation method (MAE: C=0.057, U=0.056) and density of stations (MAE: 0.063). Although this region has significantly lower precipitation than others the accuracy is clearly influenced by the variation of precipitation over the year. The highest errors occur in months with highest precipitation (July and August). Sheppard et al. (2002) states that Arizona and New Mexico receive 50% of their precipitation in the summer months from July to September. This is a part of the North American monsoon (Adams and Conrie 1997) which mainly influences mesoscale conditions making day to day forecasting difficult (Sheppard et al. 2002). The monsoon results in significantly higher errors in these months. The errors are lower in all other months where precipitation amounts are similar and evenly distributed throughout the months.

This region contains mountainous terrain towards the northern part in the states of Colorado and Utah. Intermittent topographical changes occur in Arizona and New Mexico as well and this results in overall higher errors and can be seen in the maps shown in Section 4.4. The influence of interpolation methods and density of stations is less than the influence of seasonality.

WestNorthCentral

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.39, U=0.45) followed by IDW 2.5 (MAE: C=0.41, U=0.48) and IDW 2 (MAE: C=0.45, U=0.51) and this can be seen for most combinations in Figures 4.1 and 4.2. The maximum errors occurred in July and August (MAE: C=0.47, U=0.52) and the minimum in October and November (MAE: C=0.28, U=0.32). Figure 3.7 shows that the highest average precipitation over WestNorthCentral region occurs in months of May and June (>65 mm) and lowest from November to February (<20 mm).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.19, U=0.21), interpolation method (MAE: C=0.073, U=0.073) and density of stations (MAE: 0.13). Except for the months of May and June (when precipitation is highest but errors are relatively low) the highest errors in July and August coincide with higher precipitation and lowest errors (October and November) to relatively low precipitation. This shows the significance of precipitation climatology, the precipitation distribution is a more significant factor than the amount of precipitation as small precipitation amounts distributed heterogeneously will have low spatial autocorrelation. The density of stations has a significant impact on accuracy (station density is 3 times greater for COOP than USHCN) as compared to other regions. Although the region varies from Rockies (mountainous terrain) to Great Plains the influence of interpolation methods is lower.

West

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.30, U=0.38) followed by IDW 2.5 (MAE: C=0.31, U=0.39) and IDW 2 (MAE: C=0.33, U=0.42) and this can be seen for most combinations in Figures 4.1 and 4.2. The maximum errors occurred in July and August for COOP (MAE: C=0.41), May for USHCN (MAE: U=0.43) and the minimum in December and November (MAE: C=0.25, U=0.34). Figure 3.7 shows that the highest average precipitation over West region occurs in months of December to February (>75 mm) and lowest from June to September (<10 mm).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.16, U=0.10), interpolation method (MAE: C=0.044, U=0.064) and density of stations (MAE: 0.13). The precipitation variation of this region is completely different from other regions except for Northwest. The seasonal difference of extreme errors is very low as compared to other regions especially for USHCN (MAE: U=0.10). The accuracy is affected again by spatial variation of precipitation as can be seen during the summer months. During the summer there is less precipitation, but it is highly variable spatially and therefore interpolation accuracy is lower than in other seasons. The distribution of precipitation in the western U.S. varies widely based on synoptic-scale, meso-scale and local-scale features (Mock 1996). This region has a winter precipitation regime with maximum precipitation occurring in January to March months that relates to cyclonic storms activity and the southward progression of the jet stream (Mock 1996; Trewartha 1981) and lowest precipitation occurs in the summer months. It is difficult to attribute high error in July for COOP to any particular factor. The effect of density of stations is quite significant, with the significant variation of topography and the fact that station density is very low in this region. The effect of interpolation methods is relatively small.

NorthWest

Kriging had the lowest error for 1-month SPI for all months (MAE: C=0.34, U=0.39) followed by IDW 2.5 (MAE: C=0.34, U=0.40) and IDW 2 (MAE: C=0.37, U=0.42) and this can be seen for most combinations in Figures 4.1 and 4.2. The maximum errors occurred from January through July (MAE: C=0.37, U=0.41) and then decreased, with minimum values occurring in October and November (MAE: C=0.28, U= 0.38). The highest average precipitation over NorthWest region occurs in months of November to January (>90 mm) and lowest in July and August (<20 mm).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.09, U=0.10), interpolation method (MAE: C=0.048, U=0.043) and density of stations (MAE: 0.082). The precipitation variation of this region is different from other climatic regions (except West) with lowest precipitation occurring in summer and highest in winter. This region has the lowest seasonal variation of spatial accuracy. This region has a cold season precipitation maximum occurring from November to January due to cyclonic storms originating in the Pacific (Guirguis and Avissar 2008) and dry summers. There exists significant topographic variation across this region and its effect on spatial accuracy can be observed in maps shown in Section 4.4 where the eastern part of this small region gives higher errors that cannot be seen in aggregated errors. However the variation in spatial accuracy is still lower for interpolation methods as well as station density despite the fact that this region has significant topographic variation.

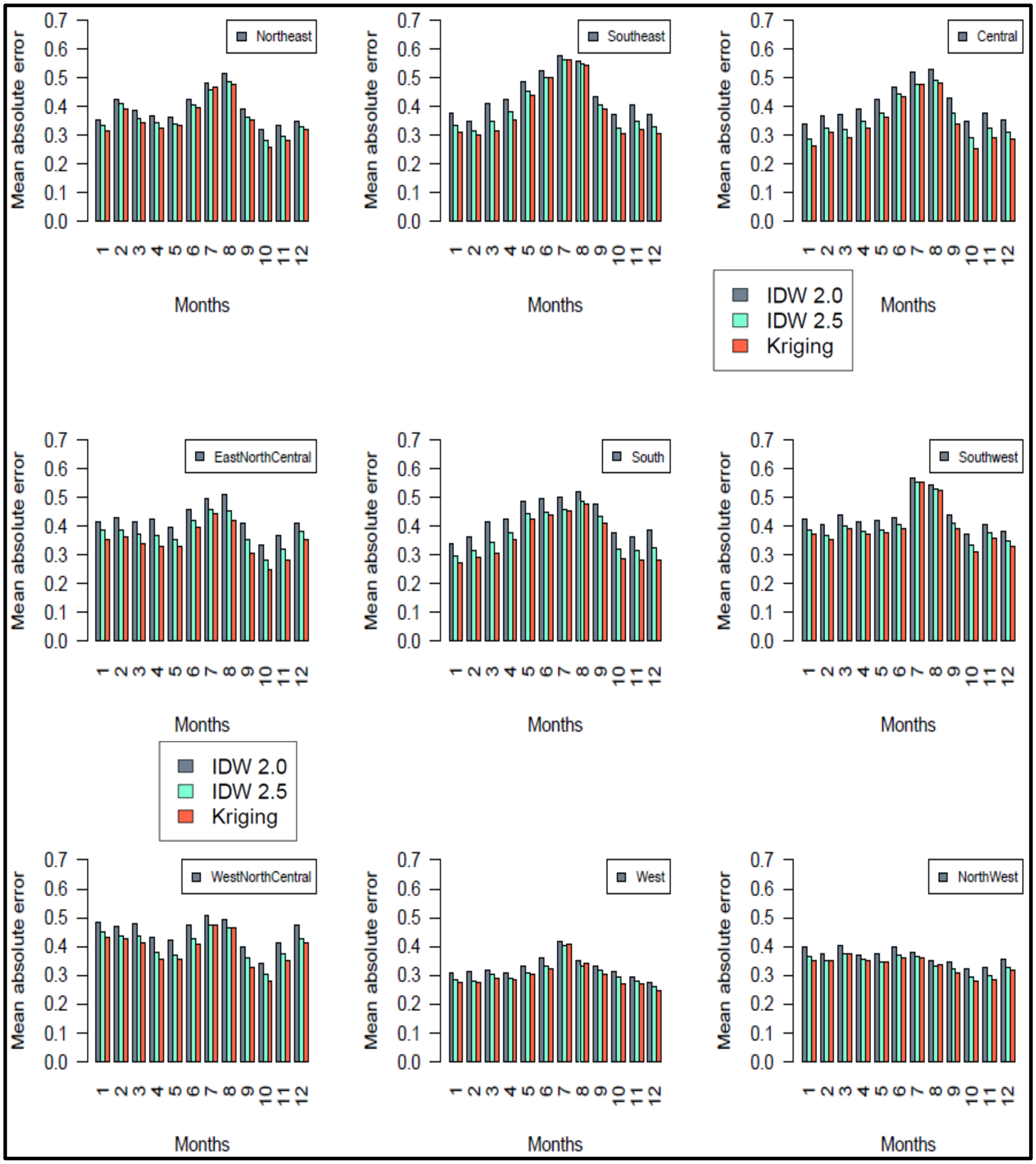

Figure 4.1 Monthly 1-month SPI for 9 climatic regions: COOP network

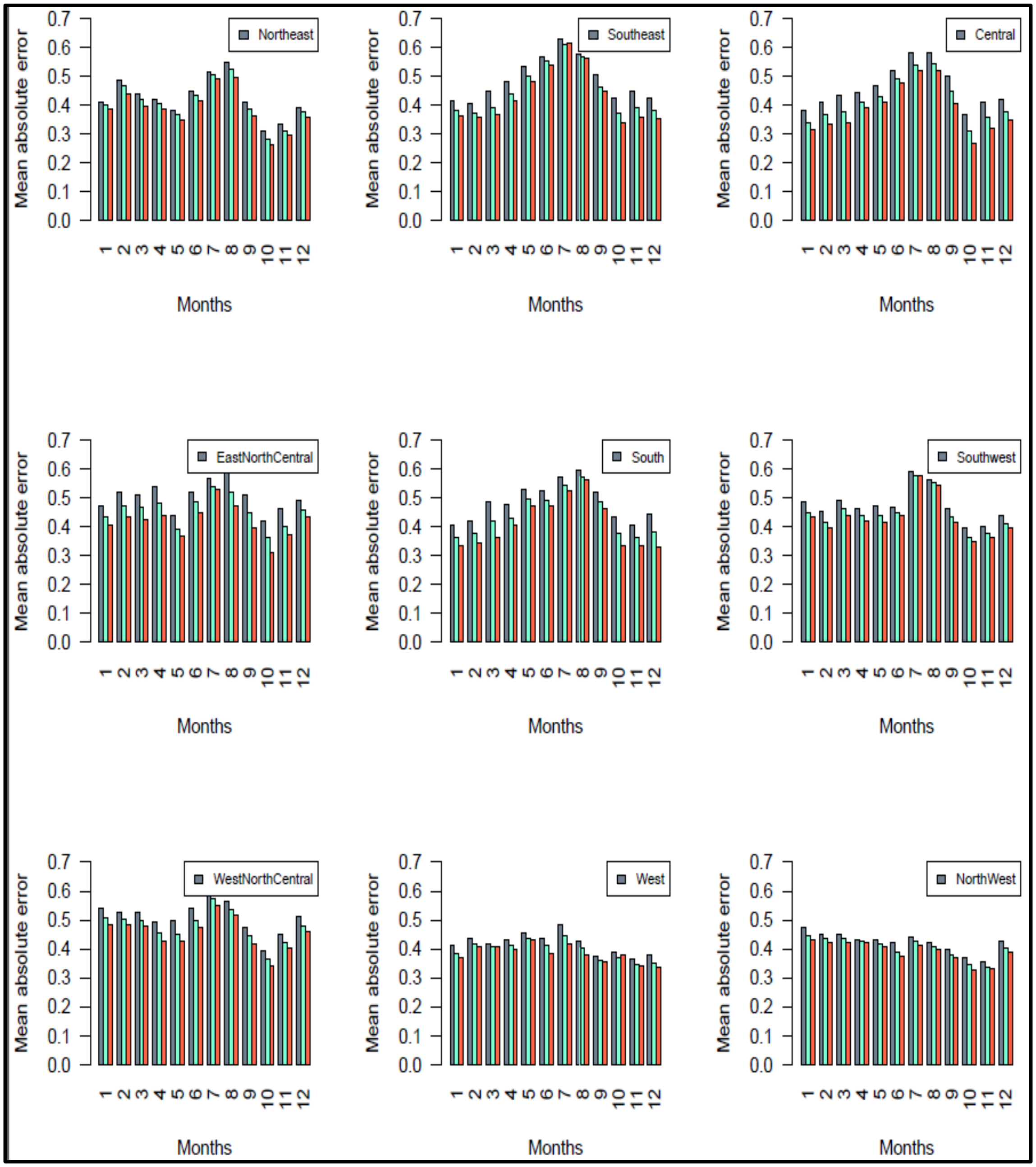

Figure 4.2 Monthly 1-month SPI for 9 climatic regions: USHCN network

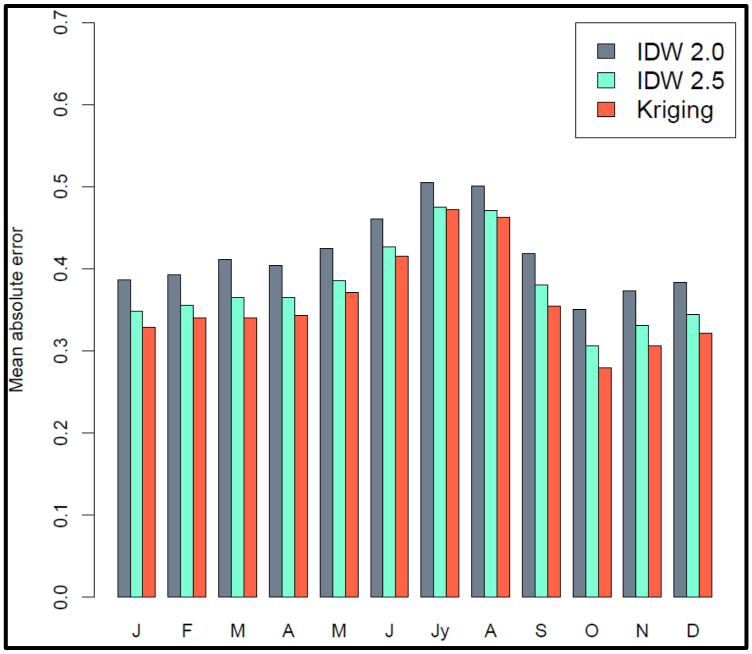

Figure 4.3 Monthly 1-month SPI averaged for the entire U.S.: COOP network

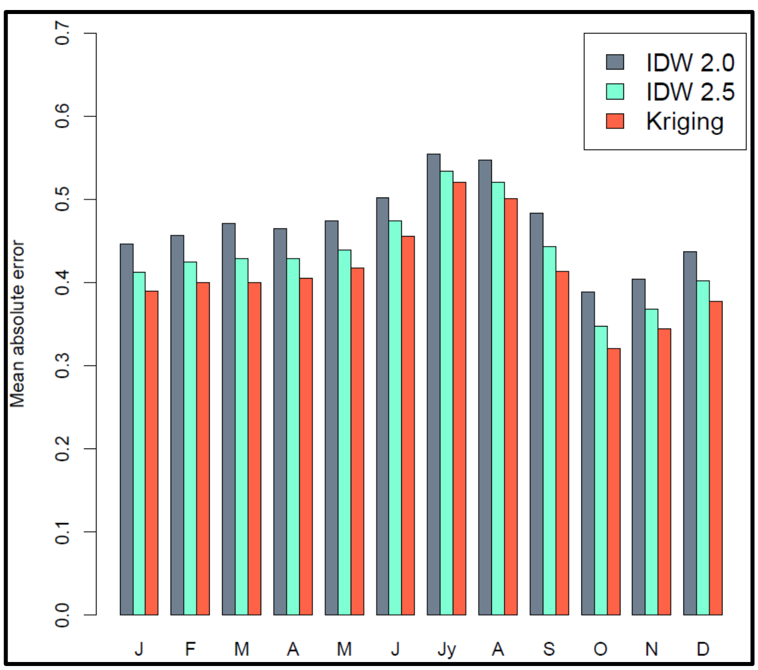

Figure 4.4 Monthly 1-month SPI averaged for the entire U.S.: USHCN network

Figures 4.3 and 4.4 show the errors for entire USA and it is clearly seen that the highest errors are observed in the months of June to August and lower values in October and November.

COOP

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.19. The average mean absolute error over the whole U.S. varies from 0.27 (October) to 0.47 (July). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.14. The average errors for the entire year vary from 0.30 (West) to 0.39 (WestNorthCentral). The lowest errors observed for a particular instance are for December in the West (0.25) and the highest for a particular instance are August in the Southeast (0.56).

USHCN

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.20. The average mean absolute error over entire USA varies from 0.32 (October) to 0.51 (July). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.14. The average errors over the entire year vary from 0.38 (West) to 0.45 (Southeast). The lowest errors observed for a particular instance are for January in the

Northeast (0.26) and the highest for a particular instance are for July in the Southeast (0.62).

The above values show that the variation of spatial accuracy is greater across seasons than climatic regions. The lowest errors amongst climatic regions are observed in the West and Northwest regions (C=0.30, U=0.39) and the highest in the WestNorthCentral and Southwest regions (C=0.38, U=0.45). The examination of results across climatic regions individually exposed particular cases where the effect of density and interpolation methods is particularly significant (e.g. West North Central region).

The West and Northwest regions with their winter precipitation regime, mountainous terrain, and proximity to the Pacific ocean, show the least variation in errors across seasons as compared to rest of the United States where seasonality is the most significant factor. In previous studies for SPI, IDW and kriging both performed equally well and better than thin plate splines (Akhtari et al. 2009; Ali et al. 2011; Carbone et al. 2008). This study, which uses the larger spatial extent of the U.S., reaffirms these findings. It also demonstrates that variations in interpolation accuracy due to seasonal variability of precipitation are larger than variations in accuracy due to the selection of the interpolation method. Chen et al. (2010) also observed that ordinary kriging and IDW performed similarly for 753 stations across China for interpolating daily precipitation. This study is similar to our case in terms of extent and station density with the only difference being the variable considered.

Since the SPI is based solely on precipitation, it is influenced the most by precipitation mechanisms and the resulting inter-annual variations in precipitation spatial heterogeneity. The results also show that climatic regions (and hence location) and station density affect the accuracy more than the choice of interpolation method.

Table 4.1 Summary of paired t-tests for 1-month SPI for 27 combinations: 9 climatic regions and 3 months, Kriging versus IDW 2.0

Result	Number of occurrences	
	COOP	**USHCN**
1 Kriging performs better than IDW 2.0 at 90% confidence level	24	22
2 IDW 2.0 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	3	5

Table 4.2 Summary of paired t-tests for 1-month SPI for 27 combinations: 9 climatic regions and 3 months, Kriging versus IDW 2.5

Result	Number of occurrences	
	COOP	**USHCN**
1 Kriging performs better than IDW 2.5 at 90% confidence level	20	22
2 IDW 2.5 performs better than Kriging at 90% confidence level	0	1
3 There is no statistically significant difference between the two methods at 90% confidence level	7	4

Table 4.3 1-month SPI**,** Mean absolute errors, COOP

	Kriging	IDW 2.0	IDW 2.5
Mean	0.36	0.42	0.38
Median	0.27	0.32	0.29

Table 4.4 1-month SPI, Mean absolute errors, USHCN

	Kriging	IDW 2.0	IDW 2.5
Mean	0.41	0.47	0.44
Median	0.31	0.36	0.33

Tables 4.1 and 4.2 show the comparison of the individual instances using paired t -tests. It is clearly seen that kriging performs better than IDW 2.5 and IDW 2.0. However as seen in Tables 4.3 and 4.4, the means of all three methods are very close and do not differ by a considerable amount.

4.1.2 1-month SPEI

The descriptions below refer to Figures 4.5 and 4.6 that shows the MAE for 1-month SPEI for 9 climatic regions. These errors are calculated for COOP and USHCN datasets. The results are analyzed for 9 climatic regions independently.

NorthEast

Kriging performed the best for 1-month SPEI for all months (MAE: C=0.34, U=0.34) followed by IDW 2.5 (MAE: C=0.35, U=0.37) and IDW 2 (MAE: C=0.38, U=0.39) and this can be seen for most combinations in Figures 4.5 and 4.6. The maximum errors occurred in February, July and August (MAE: C=0.40, U=0.44) and the minimum in October, November and May (MAE: C=0.28, U=0.27).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.12, U=0.17), interpolation method (MAE: C=0.055, U=0.053) and density of stations (MAE: 0.073). As in the case of SPI, the variation in error is driven primarily by precipitation climatology. However the variation of errors seasonally is lower in this case because of the effect of temperature. The difference between two datasets is also small.

SouthEast

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.32, U=0.31) followed by IDW 2.5 (MAE: C=0.33, U=0.33) and IDW 2 (MAE: C=0.36, U=0.37) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in July and August (MAE: C=0.37, U=0.40) and the minimum in February (MAE: C=0.24, U=0.26).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.15, U=0.14), interpolation method (MAE: C=0.079, U=0.096) and density of stations (MAE: 0.03). As in the case of SPI, the errors are affected by precipitation climatology with the months of July and August giving far higher errors than remaining months, but again the seasonal variation is considerably lower than SPI due to temperature input. The errors are slightly lower than corresponding SPI values. The effect of density of stations is negligible in this case with both datasets performing similarly.

Central

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.30, U=0.30) followed by IDW 2.5 (MAE: C=0.32, U=0.33) and IDW 2 (MAE: C=0.35, U=0.37) and this can be seen for most combinations in Figures 4.5 and 4.6. The maximum errors occurred in July for COOP (MAE: C=0.34) and December for USHCN (MAE: U=0.36) and the minimum in May (MAE: C=0.26, U=0.25).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.09, U=0.11), interpolation method (MAE: C=0.094, U=0.098) and density of stations (MAE: 0.059). The effect of precipitation climatology is important but the seasonal variation is significantly lower than for SPI. The errors are lower than for SPI. This effect of interpolation methods for both the datasets is fairly significant and although this region has the highest density of COOP stations the difference in performance of the datasets is not very high.

EastNorthCentral

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.32, U=0.37) followed by IDW 2.5 (MAE: C=0.35, U=0.41) and IDW 2 (MAE: C=0.39, U=0.46) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in August for COOP (MAE: C=0.37), February for USHCN (MAE: U= 0.44) and the minimum in October (MAE: C=0.25, U= 0.28).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.12, U=0.16), interpolation method (MAE: C=0.112, U=0.128) and density of stations (MAE: 0.10). The seasonal variation is significantly lower than SPI which is attributed to temperature input and the errors are slightly lower than corresponding SPI values. The significant difference between interpolation methods and datasets is clearly seen in these results. The COOP network has a station density that is about four times greater than USHCN and this can be observed in the difference of spatial accuracy of the two datasets.

South

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.28, U=0.27) followed by IDW 2.5 (MAE: C=0.31, U=0.30) and IDW 2 (MAE: C=0.34, U=0.35) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in October for COOP (MAE: C=0.32), January for USHCN (MAE: U=0.32) and the minimum in February for COOP (MAE: C=0.25), April for USHCN (MAE: U=0.23).

The difference between extreme errors (maximum and minimum) are:

seasonality (MAE: C=0.07, U=0.09), interpolation method (MAE: C=0.055, U=0.13) and density of stations (MAE: 0.049). The seasonal variation is again significantly lower than SPI but still an important factor in spatial accuracy. The errors are slightly lower than corresponding SPI values. USHCN performs almost as well as COOP stations. The seasonal variation is lowest amongst different regions considered for 1-month SPEI.

SouthWest

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.35, U=0.36) followed by IDW 2.5 (MAE: C=0.36, U=0.38) and IDW 2 (MAE: C=0.39, U=0.42) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in August for COOP (MAE: C=0.46), January for USHCN (MAE: U=0.46) and the minimum in May (MAE: C=0.31, U=0.29).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.15, U=0.17), interpolation method (MAE: C=0.072, U=0.085) and density of stations (MAE: 0.086). As in the case of SPI the errors are influenced by seasonal variation of precipitation climatology with highest errors occurring during the monsoon. The errors are lower than SPI for corresponding duration. The effect of station density is moderately higher as compared to other regions as is the influence of interpolation method.

WestNorthCentral

Kriging had the lowest error for 1 month SPEI for all months (MAE: C=0.31, U=0.33) followed by IDW 2.5 (MAE: C=0.32, U=0.35) and IDW 2 (MAE: C=0.35, U=0.39) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in January (MAE: C=0.36, U=0.43) and the minimum in October and November (MAE: C=0.26, U= 0.28).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.10, U=0.15), interpolation method (MAE: C=0.045, U=0.069) and density of stations (MAE: 0.064). The seasonal variation for this region is very low for 1-month SPEI. The effect of station density is less than it was for the 1-month SPI.

West

Kriging had the lowest error for 1-month SPEI for all months (MAE: C=0.32, U=0.34) followed by IDW 2.5 (MAE: C=0.33, U=0.36) and IDW 2 (MAE: C=0.35, U=0.39) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in July and August (MAE: C=0.45, U=0.44) and the minimum error in April (MAE: C=0.25, U=0.28).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.20, U=0.16), interpolation method (MAE: C=0.064, U=0.068) and density of stations (MAE: 0.101). Even with a winter precipitation regime, the highest errors occur in June and July and the seasonal variation is slightly higher than SPI. The effect of station density is significant in this case.

NorthWest

Kriging performed better for 1-month SPEI for all months (MAE: C=0.33, U=0.35) followed by IDW 2.5 (MAE: C=0.34, U=0.36) and IDW 2 (MAE: C=0.36, U=0.38) and this can be seen for all combinations in Figures 4.5 and 4.6. The maximum errors occurred in January (MAE: C=0.36, U=0.45) and the minimum in November for COOP (MAE: C=0.30), May for USHCN (MAE: U=0.29).

The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.06, U=0.15), interpolation method (MAE: C=0.065, U=0.067) and density of stations (MAE: 0.087). As in the case of SPI, the errors are affected by monthly variations in precipitation. The seasonal variation is slightly lower than SPI for COOP and slightly higher than USHCN. The highest errors coincide with months of high precipitation. The errors are slightly lower than corresponding SPI values and the influence of station density is important.

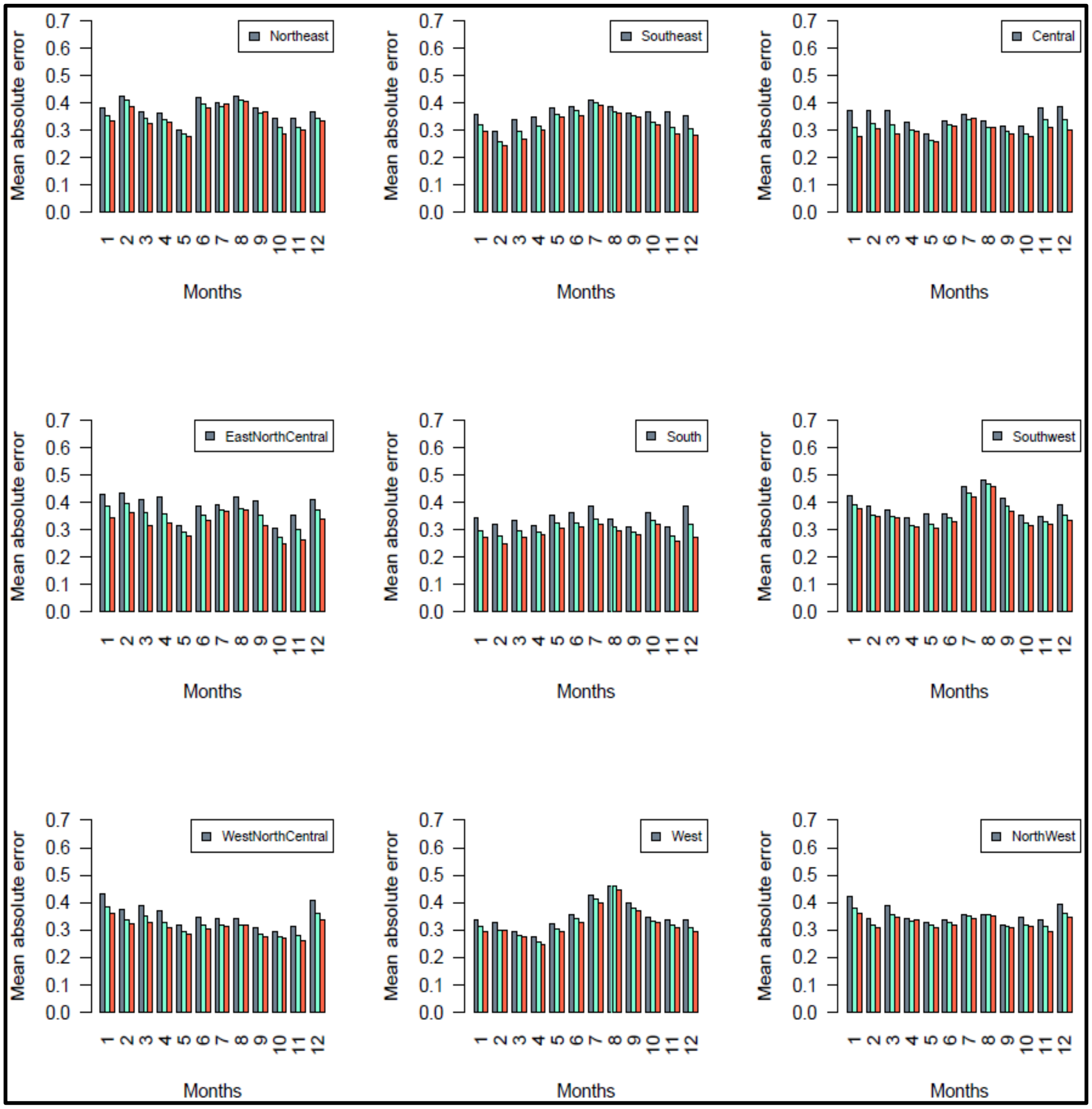

Figure 4.5 Monthly 1-month SPEI for 9 climatic regions: COOP network

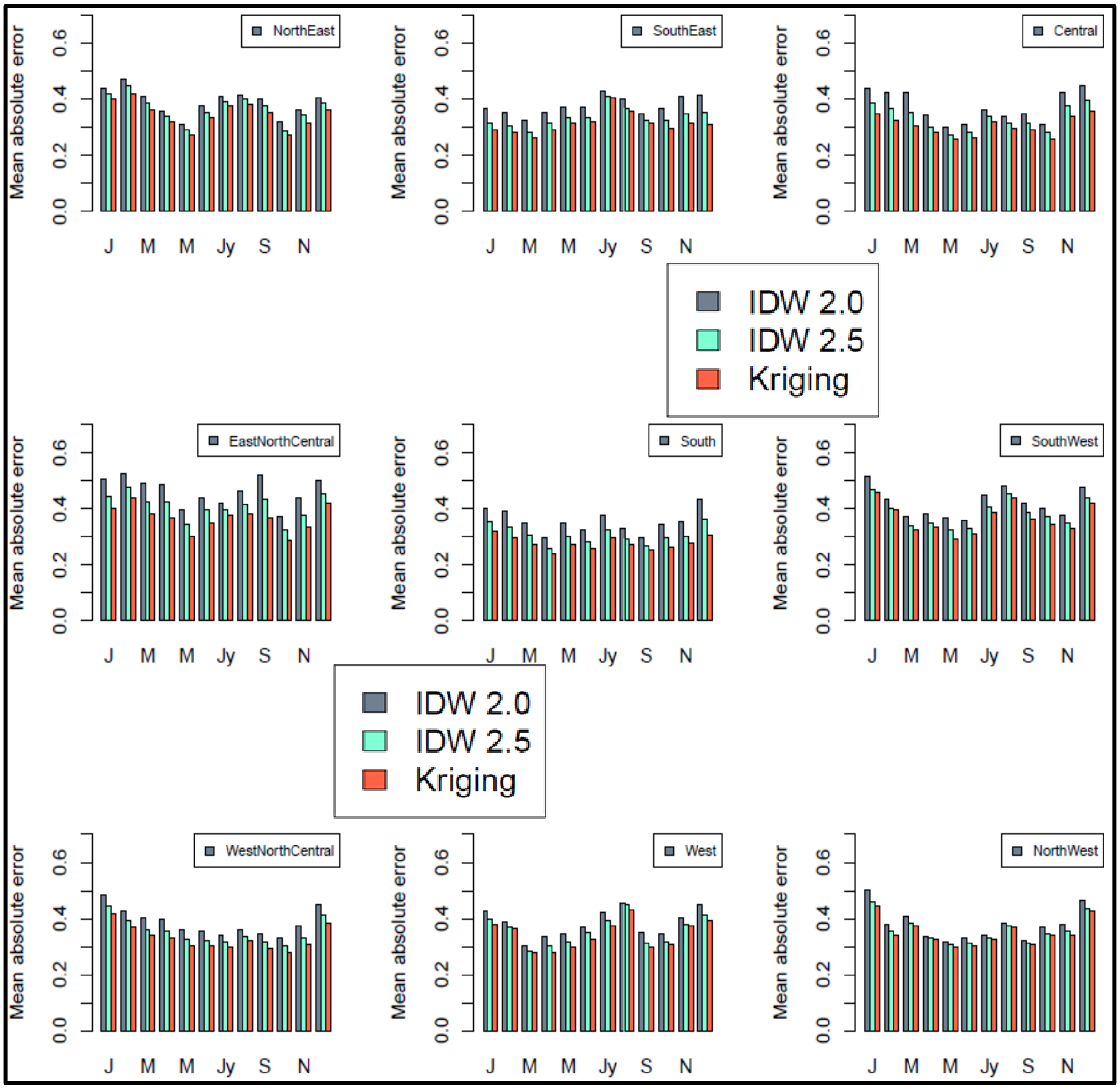

Figure 4.6 Monthly 1-month SPEI for 9 climatic regions: USHCN network

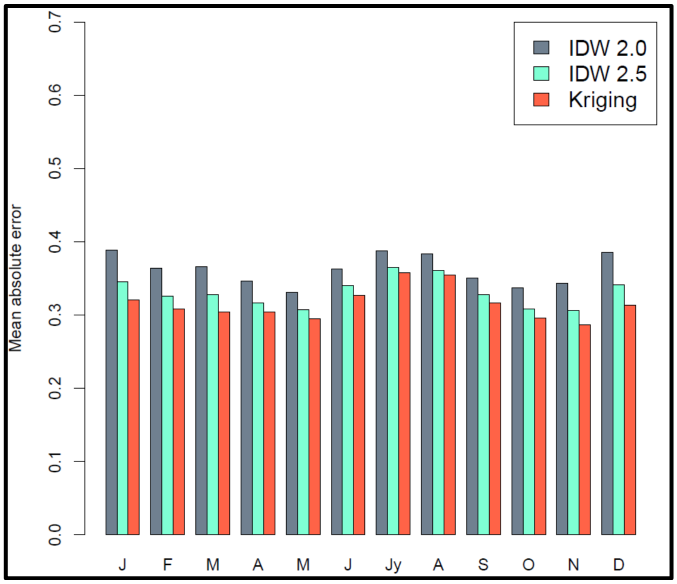

Figure 4.7 Monthly 1-month SPEI averaged for the entire U.S.: COOP network

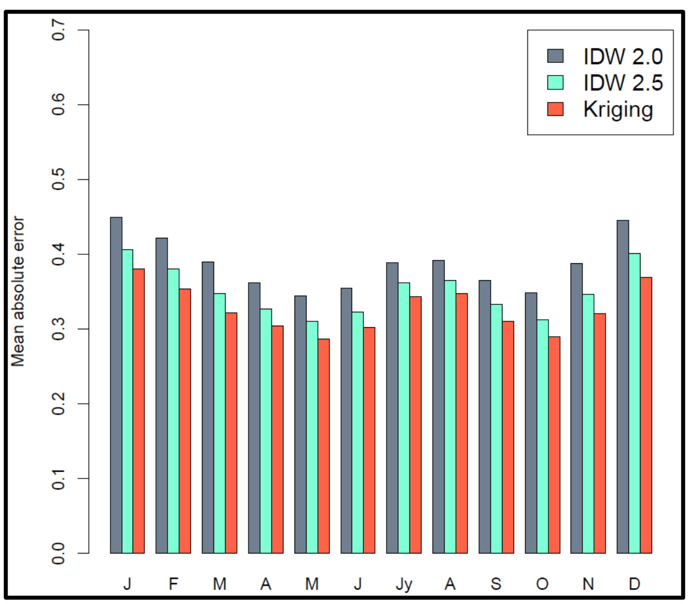

Figure 4.8 Monthly 1-month SPEI averaged for the entire U.S.: USHCN network

Figures 4.7 and 4.8 show the variation of 1-month SPEI average over the entire United States.

COOP

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.12. The average mean absolute errors over the U.S. vary from 0.29 (November, October) to 0.37 (July, August). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.10. The average errors over the entire year vary from 0.29 (South) to 0.35 (Southwest). The lowest errors observed for a particular instance is for February month in the Southeast (0.24) and the highest for a particular instance is for August in the Southwest (0.46).

USHCN

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.15. The average mean absolute errors over the U.S. vary from 0.29 (May, October) to 0.39 (January). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.12. The average errors over the entire year vary from 0.27 (South) to 0.37 (East North Central). The lowest errors observed for a particular instance is for April in the South (0.23) and the highest for a particular instance is for January in the Southwest (0.46).

The above results confirm that there are larger variations in spatial accuracy across seasons than climatic regions and the variations in spatial accuracy for 1-month SPEI are lower than 1-month SPI. The climatic region results exposed particular cases where the effect of density and interpolation methods is particularly strong.

Since the SPEI is a drought index that depends on both precipitation and temperature it can be interpolated more accurately than the 1-month SPI. The self-calibrated PDSI and SPEI can detect drought caused by water demand (evapotranspiration). Because the self-calibrated PDSI measures more of a long-term drought signal, it also has relatively lower seasonal and spatial (over climatic regions) variation than the 1-month SPI as can be seen in Section 4.1.3.

The influence of station density, and climatic regions are lower for the SPEI than the SPI due to the impact of temperature on its calculation. The effect of station density and interpolation methods are less for the 1-month SPEI, but the best options available (e.g., ordinary kriging and COOP) should be used to achieve the highest accuracy.

Table 4.5 Summary of paired t-tests for 1-month SPEI: 9 climatic regions * 3 months = 27 combinations**,** Kriging versus IDW 2.0

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Kriging performs better than IDW 2.0 at 90% confidence level	25	27
2 IDW 2.0 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	2	0

Table 4.6 Summary of paired t-tests for 1-month SPEI: 9 climatic regions * 3 months = 27 combinations**,** Kriging versus IDW 2.5

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Kriging performs better than IDW 2.5 at 90% confidence level	20	25
2 IDW 2.5 performs better than Kriging at 90% confidence level	1	0
3 There is no statistically significant difference between the two methods at 90% confidence level	6	2

Table 4.7 1-month SPEI, Mean absolute errors, COOP

	Kriging	IDW 2.0	IDW 2.5
Mean	0.31	0.36	0.33
Median	0.24	0.29	0.26

Table 4.8 1-month SPEI, Mean absolute errors, USHCN

	Kriging	IDW 2.0	IDW 2.5
Mean	0.33	0.39	0.35
Median	0.25	0.31	0.27

Tables 4.5 and 4.6 show the results of paired t-tests used to compare different interpolation methods for different instances of 1-month SPEI. Kriging clearly performs better than IDW 2.5 and IDW 2.0, however as seen in Tables 4.7 and 4.8 the differences are small. The difference in accuracy of interpolation methods is not the most significant factor affecting spatial accuracy of 1-month SPEI.

4.1.3. Self-calibrated PDSI

The descriptions below refer to Figures 4.9 to 4.12 that show the variation across 9 climatic regions and 12 months of self-calibrated PDSI for USHCN and COOP datasets. As the PDSI is not standardized the same way as SPI and SPEI, the errors are not directly compared with the corresponding SPI and SPEI values. Only comparisons of relative influence of different factors are made in this section. The PDSI represents more long-term moisture trends than the 1-month SPI and SPEI, but may be compared to 6-, 9- or 12-month SPI and SPEI.

NorthEast

Kriging had the lowest error for PDSI for all months (MAE: C=1.00, U=1.13) followed by IDW 2.5 (MAE: C=1.25, U=1.16) and IDW 2 (MAE: C=1.27, U=1.19) and this can be seen for all combinations in Figures 4.9 and 4.10.The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.19, U=0.20), interpolation method (MAE: C=0.31, U=0.08) and density of stations (MAE: 0.06). The seasonal variation is significant for both datasets and clearly changes in seasonal precipitation patterns produce significant variations in spatial accuracy. Although the errors are not standardized, and the PDSI has higher errors, it can be seen that the seasonal variation in errors for the PDSI is lower than for 1-month SPI and comparable to 1-month SPEI. The difference between interpolation methods is very high for the COOP dataset, with kriging performing far better than IDW 2.5 or IDW 2.0

SouthEast

Kriging had the lowest error for PDSI for all months (MAE: U=0.87, C=1.14) followed by IDW 2.5 (MAE: C=1.20, U=1.16) and IDW 2 (MAE: C=1.24, U=1.23) and this can be seen for all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.20, U=0.21), interpolation method (MAE: C=0.42, U=0.11) and density of stations (MAE: 0.25). The seasonal variation is significant for both datasets and seasonal variations in precipitation drives variations in spatial accuracy. The difference between interpolation methods is again very high for the COOP dataset with kriging performing far better than either IDW 2.5 or IDW 2.0, this difference is lower for USHCN. The difference of errors between the datasets is also significant in this region.

Central

Kriging had the lowest error for PDSI for all months (MAE: C=0.90, U=1.04) followed by IDW 2.5 (MAE: C=1.16, U=1.10) and IDW 2 (MAE: C=1.22, U=1.15) and this can be seen for almost all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.14, U=0.12), interpolation method (MAE: C=0.39, U=0.18) and density of stations (MAE: 0.11). The seasonal variation is low for both datasets. The seasonal variation for PDSI is lower than the corresponding variation for 1-month SPI and 1-month SPEI. The difference between interpolation methods is large for the COOP dataset with kriging performing better than either IDW 2.5 or IDW 2.0. The difference between interpolation methods is lower for USHCN, but still higher than other regions. The difference of errors between the datasets is fairly low in this region.

EastNorthCentral

Kriging had the lowest error for PDSI for all months (MAE: C=0.86, U=1.09) followed by IDW 2.5 (MAE: C=1.05, U=1.15) and IDW 2 (MAE: C=1.12, U=1.24) and this can be seen for all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.11, U=0.12), interpolation method (MAE: C=0.29, U=0.18) and density of stations (MAE: 0.17). The seasonal variation is low in this region. The seasonal variation is lower for PDSI than for 1-month SPI and 1-month SPEI. The difference between interpolation methods is large for both COOP and USHCN datasets with kriging performing far better than either IDW 2.5 or IDW 2.0. The difference between the datasets is not large when compared to other regions.

South

Kriging had the lowest error for PDSI for all months (MAE: C=0.95, U=1.09) followed by IDW 2.5 (MAE: C=1.22, U=1.12) and IDW 2 (MAE: C=1.27, U=1.19) and this can be seen for all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.10, U=0.18), interpolation method (MAE: C=0.34, U=0.14) and density of stations (MAE: 0.082). The seasonal variation is not large, although the extreme values for USHCN are almost twice that of COOP. The seasonal variation in PDSI is lower than for 1-month SPI and 1-month SPEI. The difference between interpolation methods is quite large for the COOP dataset with kriging performing far better than either IDW 2.5 or IDW 2.0, but the difference between interpolation methods is much less for USHCN. The difference of errors between the USHCN and COOP datasets is not very large in this region.

SouthWest

Kriging had the lowest error for PDSI for all months (MAE: C=0.96, U=1.09) followed by IDW 2.5 (MAE: C=1.19, U=1.09) and IDW 2 (MAE: C=1.21, U=1.13) and this can be seen for most combinations in Figures 4.9 and 4.10.T he difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.14, U=0.26), interpolation method (MAE: C=0.29, U=0.06) and density of stations (MAE: 0.052). The seasonal variation is lower for COOP and almost twice as large for USHCN. The seasonal variation in PDSI is lower than for 1-month SPI and 1-month SPEI. The difference between interpolation methods is quite large for the COOP dataset with kriging performing far better than both IDW 2.5 and IDW 2.0, however the differences between interpolation methods are almost nonexistent for USHCN. The difference in spatial accuracy between the USHCN and COOP datasets is less in this region.

WestNorthCentral

Kriging had the lowest error for PDSI for all months (MAE: C=0.94, U=1.09) followed by IDW 2.5 (MAE: C=1.15, U=1.11) and IDW 2 (MAE: C=1.17, U=1.13) and this can be seen for all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.104, U=0.20), interpolation method (MAE: C=0.26, U=0.06) and density of stations (MAE: 0.034). The seasonal variation is lower for this region and the extreme errors for USHCN are almost twice as large as COOP. The difference between interpolation methods is quite large for the COOP dataset with kriging performing far better than either IDW 2.5 or IDW 2.0, but the differences are trivial for USHCN. The difference of errors between the datasets is also insignificant.

West

Kriging had the lowest error for PDSI for all months (MAE: C=0.83, U=1.10) followed by IDW 2.5 (MAE: C=1.07, U=1.15) and IDW 2 (MAE: C=1.10, U=1.19) and this can be seen for all combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.12, U=0.27), interpolation method (MAE: C=0.29, U=0.10) and density of stations (MAE: 0.17). The seasonal variation is relatively higher for USHCN network and very low for COOP network as is shown by the extreme values. The difference between interpolation methods is quite large for the COOP dataset with kriging performing far better than either IDW 2.5 or IDW 2.0, but these differences are not as large for USHCN. COOP provides a fair amount of improvement in spatial accuracy as compared to USHCN.

NorthWest

Kriging had the lowest errors for PDSI for all months (MAE: C=0.92, U=1.05) followed by IDW 2.5 (MAE: C=1.15, U=1.12) and IDW 2 (MAE: C=1.15, U=1.11) and this can be seen for most combinations in Figures 4.9 and 4.10. The difference between extreme errors (maximum and minimum) are: seasonality (MAE: C=0.10, U=0.13), interpolation method (MAE: C=0.24, U=0.07) and density of stations (MAE: 0.06). The seasonal variation in this region is minimal for both the USHCN and COOP datasets. The difference between interpolation methods are large for the COOP dataset, with kriging performing far better than either IDW 2.5 or IDW 2.0, but they are minimal for USHCN. The difference of errors between the datasets is low in this region.

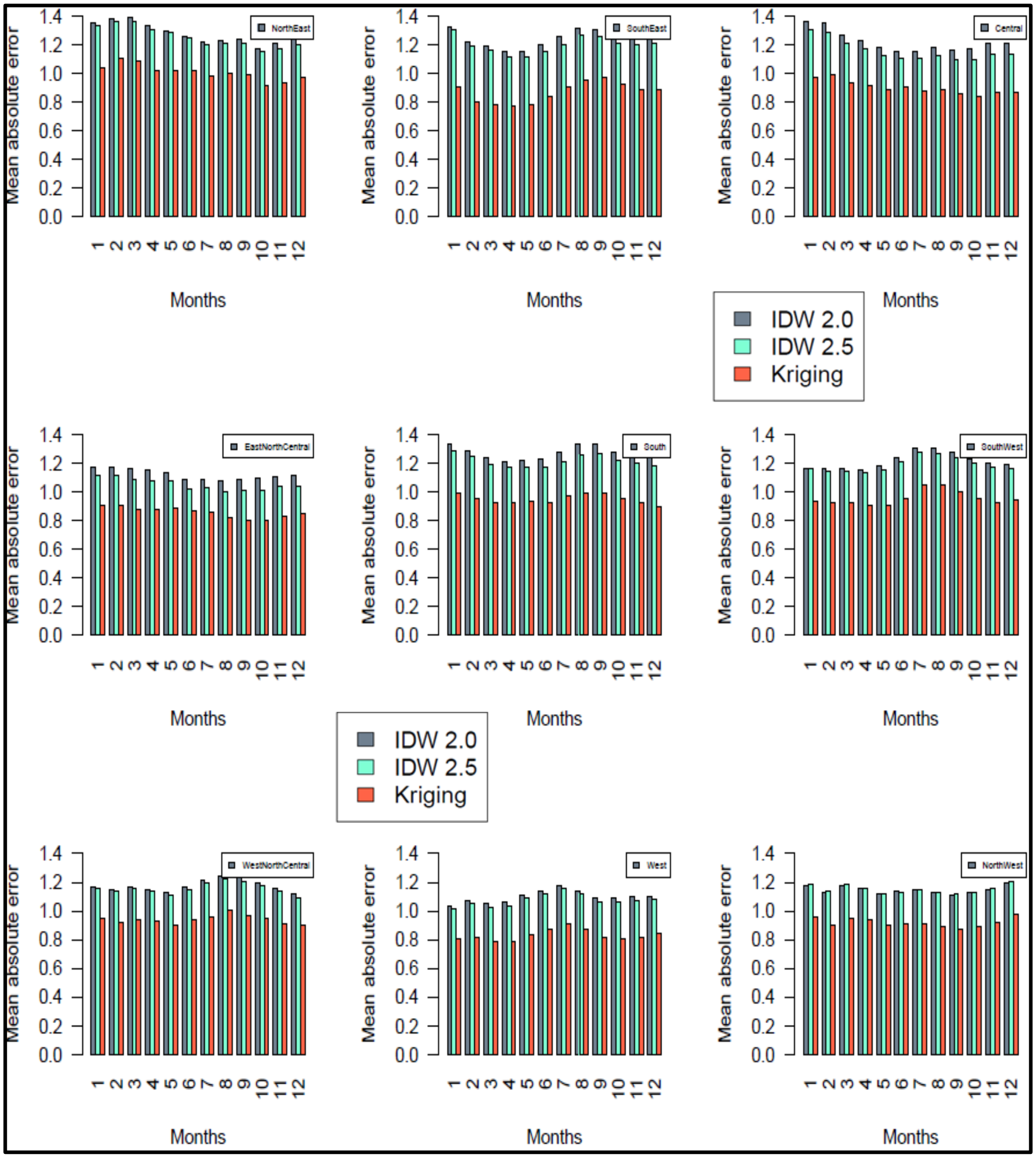

Figure 4.9 Monthly PDSI for 9 climatic regions: COOP network

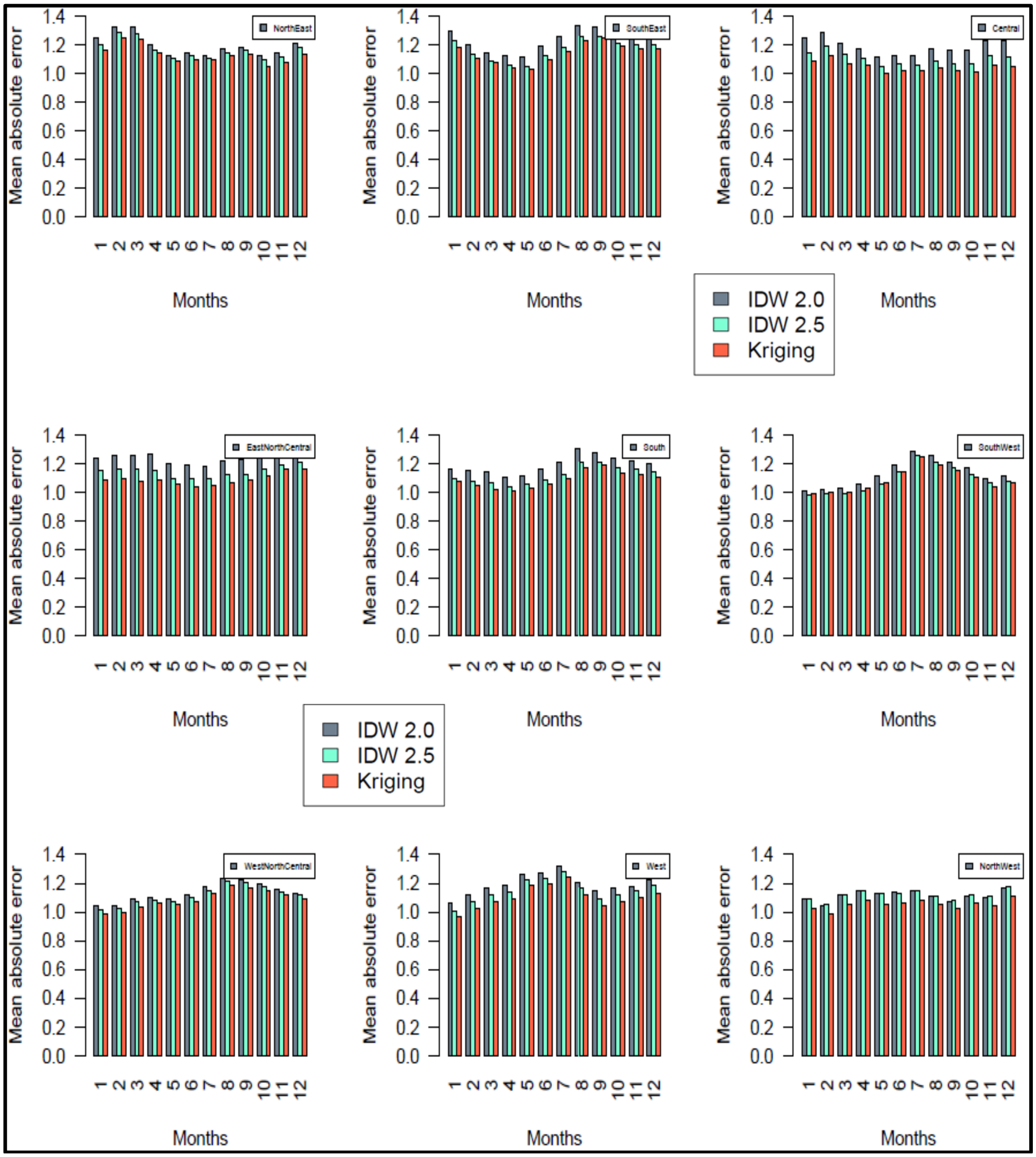

Figure 4.10 Monthly PDSI for 9 climatic regions: USHCN network

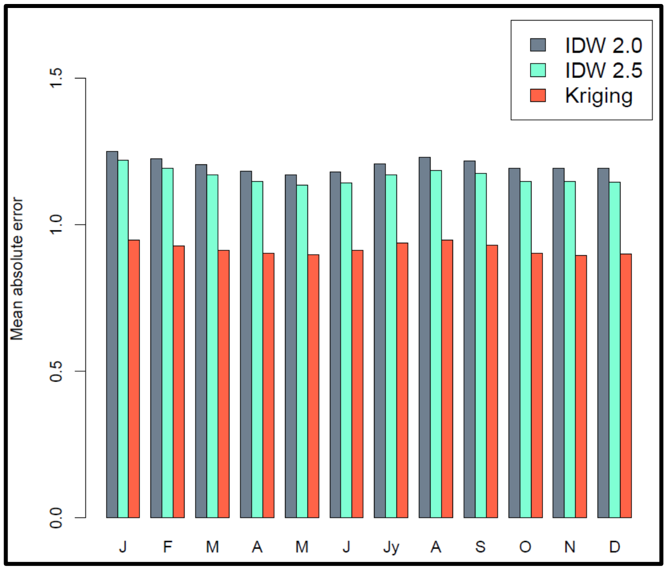

Figure 4.11 Monthly PDSI averaged over the U.S.: COOP network

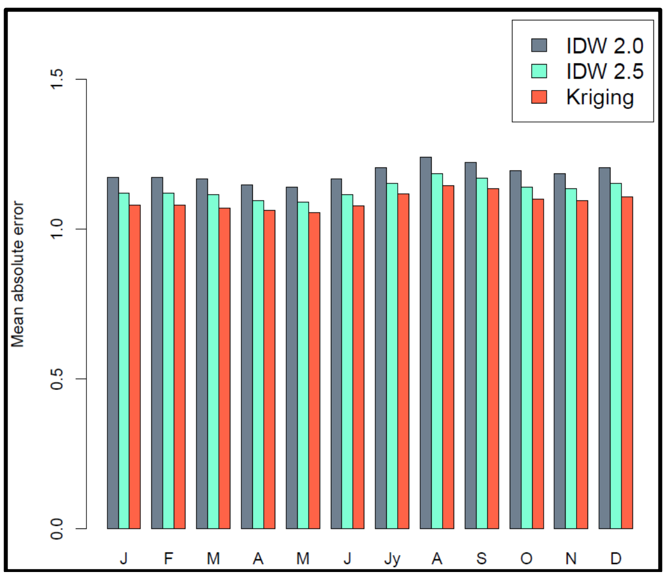

Figure 4.12 Monthly PDSI averaged over the U.S.: USHCN network

Figures 4.11 and 4.12 show the variation of mean absolute errors over 9 climatic regions for PDSI over entire U.S. They reaffirm the previous results described above for each climatic region. The seasonal variation for PDSI is very low when compared to 1-month SPI and 1-month SPEI values. This is because PDSI represents long-term moisture conditions as compared to the monthly SPI and SPEI. The difference between interpolation methods is much more important for the COOP network as compared to USHCN.

COOP

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.13. The average mean absolute errors over entire U.S. vary from 0.89 (November) to 0.94 (January). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.21. The average errors over the entire year vary from 0.83 (NorthWest) to 1.00 (NorthEast). The lowest errors observed for a particular instance is for April in Southeast (0.77) and the highest for a particular instance is February in Northeast (1.10).

USHCN

The average of the difference of extreme seasonal values (maximum and minimum for 12 months) for every instance calculated individually over 9 climatic regions is 0.19. The average mean absolute errors over entire U.S. vary from 1.06 (May) to 1.13 (August). The corresponding average of extreme errors between climatic regions (maximum and minimum for 9 regions) for every instance calculated over 12 months is 0.19. The average errors over entire year vary from 1.04 (Central) to 1.13 (Southeast). The lowest errors observed for a particular instance is for January in West (0.97) and the highest for a particular instance is July in Southwest (1.25).

COOP has higher variations in error across the climatic regions than across the seasons. For USHCN, there were only minor differences in the magnitude of the errors for the climatic regions versus the seasons. The maps in Section 4.4 show there are significant local variations in errors for COOP that are not present in USHCN. This means that although the error values for the two datasets are similar, the performance varies substantially at the local scale. Therefore, a finer scale examination of spatial variations in interpolation accuracy is necessary for PDSI.

The spatial accuracy of the interpolation varies due to a number of factors. It is clear that interpolation methods significantly influence the accuracy of interpolation using the COOP network and this is more significant than the variation of spatial accuracy by season or by networks. Carbone et al. (2008) have shown that IDW and kriging both had similar accuracy for interpolating PDSI over North and South Carolina. Sensitivity studies of PDSI have shown it to be significantly dependent on the weighting factor (Heim 2002), the value for available water holding capacity of the soil (Karl 1983) and the calibration period used for calculation (Karl et al. 1987). COOP contains few stations with significantly higher lengths (>50 years), whereas most of the USHCN stations contain a good long term record. These differences influence the calculation of

PDSI and account for the performance difference between COOP and USHCN networks.

Table 4.9 Summary of paired t-tests for PDSI: 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.0

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Kriging performs better than IDW 2.0 at 90% confidence level	26	27
2 IDW 2.0 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	1	0

Table 4.10 Summary of paired t-tests for PDSI: 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.5

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Kriging performs better than IDW 2.5 at 90% confidence level	27	23
2 IDW 2.5 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	0	4

Table 4.11 PDSI, Mean absolute errors, COOP

	Kriging	IDW 2.0	IDW 2.5
Mean	0.92	1.20	1.16
Median	0.63	0.99	0.92

Table 4.12 PDSI, Mean absolute errors, USHCN

	Kriging	IDW 2.0	IDW 2.5
Mean	1.09	1.18	1.13
Median	0.86	0.99	0.9

Tables 4.9 and 4.10 demonstrate that kriging is better than IDW 2.0 and IDW 2.5 in almost all cases. Tables 4.11 and 4.12 show that the difference in interpolation accuracy between different interpolation methods is small for USHCN, but it is much more important for COOP. This suggests that the main factor limiting the accuracy of the USHCN interpolations is station density, while the higher density of COOP makes the selection of interpolation methods more important.

4.1.4. 6-, 9- and 12-month SPI

The descriptions below refer to Figures 4.13 to 4.16 that show the variations of 6-, 9- and 12-month SPI over 9 climatic regions for two datasets. Only January, July and October months are used for comparison.

NorthEast

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.39, U=0.25) followed by IDW 2.5 (MAE: C=0.41, U=0.26) and IDW 2 (MAE: C=0.43, U=0.26) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.41, U=0.28) to a minimum of (MAE: C=0.37, U=0.22) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation methods (MAE: C=0.047, U=0.028) and density of stations (MAE: 0.17). USHCN performs better than COOP for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI, but this is not true for COOP. The errors for most of the combinations have similar magnitudes.

SouthEast

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.42, U=0.37) followed by IDW 2.5 (MAE: C=0.44, U=0.38) and IDW 2 (MAE: C=0.47, U=0.39) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.46, U=0.41) to minimum values of (MAE: C=0.40, U=0.28) among the time scales considered.

The difference between extreme errors (maximum and minimum) are:

interpolation method (MAE: C=0.052, U=0.027) and density of stations (MAE: 0.12). USHCN performs better than COOP for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI, but this is not true for COOP.

Central

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.38, U=0.27) followed by IDW 2.5 (MAE: C=0.40, U=0.28) and IDW 2 (MAE: C=0.45, U=0.28) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.39, U=0.30) to a minimum of (MAE: C=0.35, U=0.24) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.08, U=0.02) and density of stations (MAE: 0.14). USHCN performs better than COOP for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI. This is not the case for COOP, whose values for all the combinations are similar.

EastNorthCentral

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.40, U=0.21) followed by IDW 2.5 (MAE: C=0.42, U=0.25) and IDW 2 (MAE: C=0.47, U=0.29) and this can be seen for all combinations in Figures 4.13 and 4.14. The seasonal errors varied from a maximum of (MAE: C=0.41, U=0.26) to a minimum of (MAE: C=0.35, U=0.19) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are:

interpolation method (MAE: C=0.08, U=0.091) and density of stations (MAE: 0.22). USHCN performs better than COOP for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI, but the same does not hold true for COOP.

South

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.38, U=0.31) followed by IDW 2.5 (MAE: C=0.41, U=0.32) and IDW 2 (MAE: C=0.46, U=0.34) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.41, U=0.32) to a minimum of (MAE: C=0.36, U=0.28) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.09, U=0.048) and density of stations (MAE: 0.10). The USHCN stations perform far better than COOP stations for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI, but the same case does not hold true for COOP.

SouthWest

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.46, U=0.32) followed by IDW 2.5 (MAE: C=0.48, U=0.34) and IDW 2 (MAE: C=0.50, U=0.36) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.49, U=0.35) to a minimum of (MAE: C=0.44, U = 0.28) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are:

interpolation method (MAE: C=0.04, U=0.056) and density of stations (MAE: 0.18). USHCN performs better than COOP for all cases. The error values for multiscalar SPI for USHCN are lower than corresponding values for 1-month SPI and SPEI.

WestNorthCentral

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.42, U=0.25) followed by IDW 2.5 (MAE: C=0.44, U=0.27) and IDW 2 (MAE: C=0.47, U=0.28) and this can be seen for most combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.44, U=0.29) to a minimum of (MAE: C=0.41, U=0.22) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.06, U=0.033) and density of stations (MAE: 0.21). USHCN performs better than COOP stations for all cases. The error values for multiscalar SPI for USHCN are lower than for 1-month SPI and SPEI. This does not hold true for COOP.

West

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.31, U=0.39) followed by IDW 2.5 (MAE: C=0.33, U=0.40) and IDW 2 (MAE: C=0.35, U=0.42) and this can be seen for all combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.41, U=0.41) to a minimum of (MAE: C=0.28, U=0.35) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are:

interpolation method (MAE: C=0.05, U=0.037) and density of stations (MAE: 0.11). The overall errors for COOP are lower than USHCN in this case. The seasonal variation in interpolation errors for USHCN is quite low.

NorthWest

Kriging had the lowest error for 6-, 9- and 12-month SPI for all months (MAE: C=0.37, U=0.32) followed by IDW 2.5 (MAE: C=0.39, U=0.34) and IDW 2 (MAE: C=0.41, U=0.34) and this can be seen for most combinations in Figures 4.13 and 4.14. The errors vary from a maximum of (MAE: C=0.39, U=0.41) to a minimum of (MAE: C=0.35, U=0.28) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.05, U=0.17) and density of stations (MAE: 0.09). USHCN performs better than COOP for all cases. The network is still the most critical factor that affects interpolation accuracy.

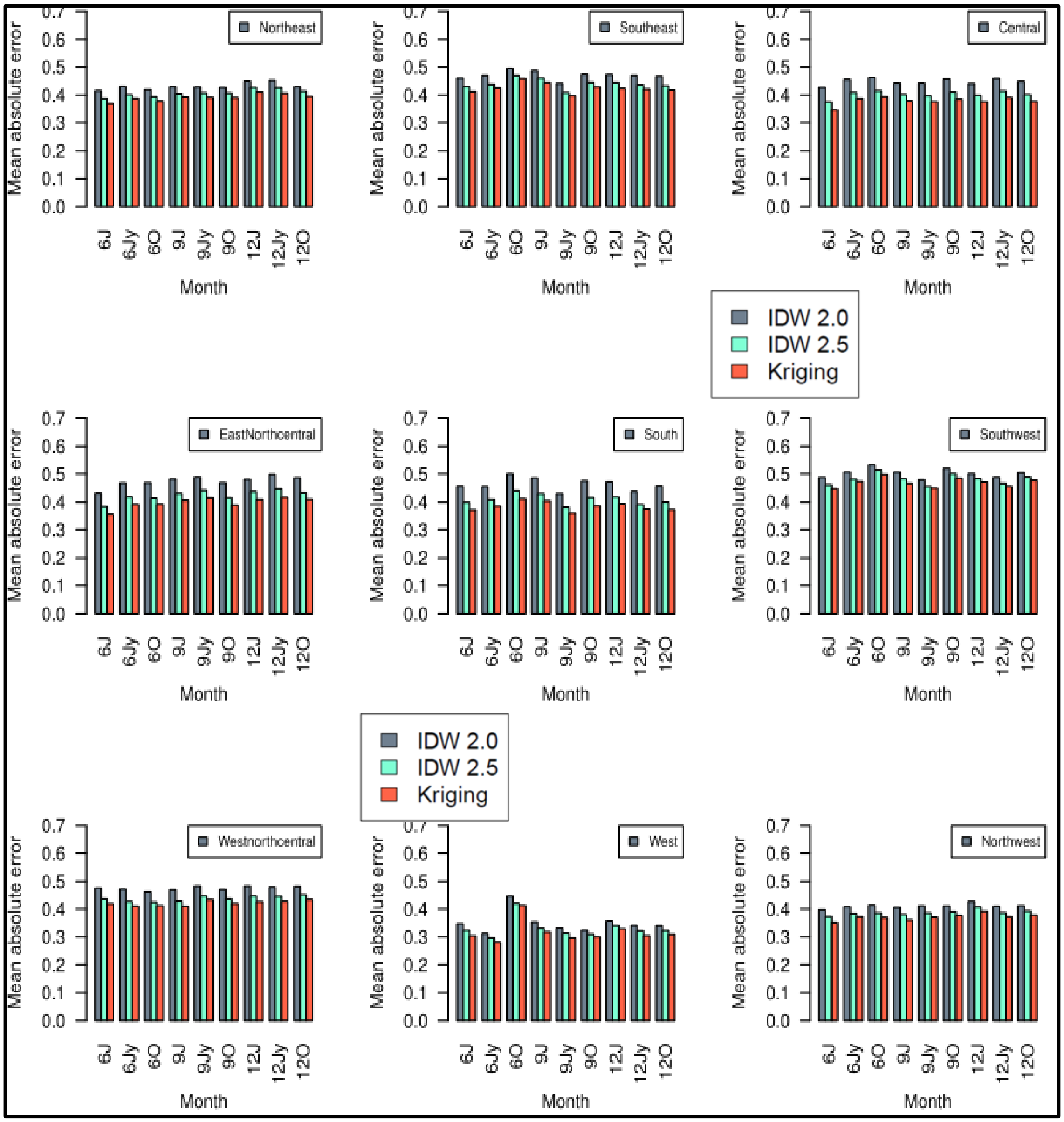

Figure 4.13 Monthly 6-, 9- and 12-month SPI for 9 climatic regions: COOP network

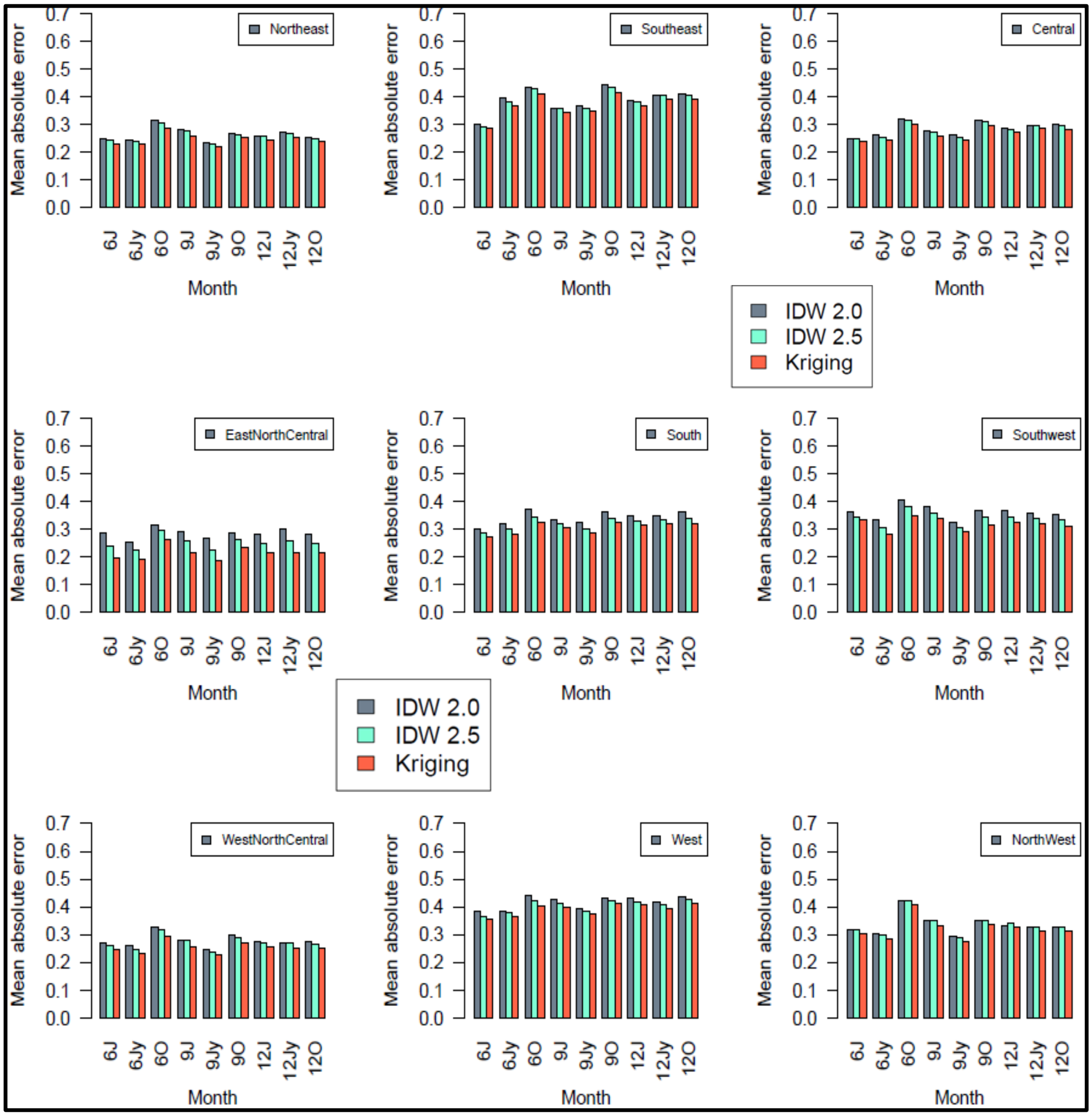

Figure 4.14 Monthly 6-, 9- and 12-month SPI for 9 climatic regions: USHCN network

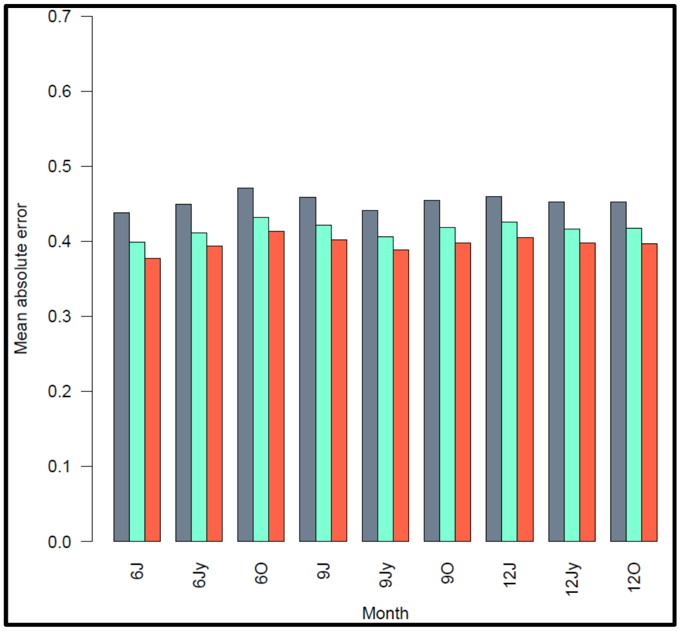

Figure 4.15 6-, 9- and 12-month SPI for January (J), July (Jy) and October (O) averaged across U.S.: COOP network

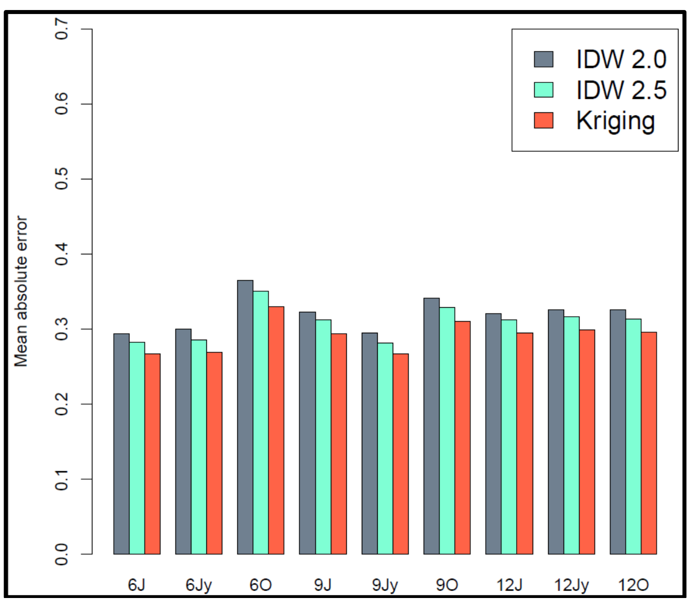

Figure 4.16 6-, 9- and 12-month SPI for January (J), July (Jy) and October (O) averaged across U.S.: USHCN network

Figures 4.13 to 4.16 show the mean absolute errors for multiscalar for January, July and October across 9 climatic regions and aggregated over the entire U.S. for both COOP and USHCN datasets. The error values are lower for USHCN than COOP. This is despite the fact that USHCN has a lower density of stations. For both 1-month SPI and 1-month SPEI, COOP had slightly lower errors than USHCN for most instances. The effect of interpolation methods on the overall accuracy is minimal.

The variation of values amongst different month-index combinations is lower for COOP as compared to USHCN dataset. Relatively higher errors for multiscalar SPI with USHCN data were observed in Southeast and West regions. The western region is an outlier for both USHCN and COOP datasets with it showing slightly lower errors than other climatic regions for COOP and vice-versa for USHCN.

Table 4.13 Summary of paired t-tests for multiscalar SPI: 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.0

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Kriging performs better than IDW 2.0 at 90% confidence level	75	80
2 IDW 2.0 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	6	1

Table 4.14 Summary of paired t-tests for multiscalar SPI: 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.5

Result	Number of occurrences COOP	Number of occurrences USHCN
1 Kriging performs better than IDW 2.5 at 90% confidence level	61	72
2 IDW 2.5 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	20	9

Table 4.15 Multiscalar SPI, Mean absolute errors, COOP

	Kriging	IDW 2.0	IDW 2.5
Mean	0.40	0.45	0.42
Median	0.32	0.37	0.34

Table 4.16 Multiscalar SPI, Mean absolute errors, USHCN

	Kriging	IDW 2.0	IDW 2.5
Mean	0.29	0.32	0.31
Median	0.22	0.25	0.24

Tables 4.13 and 4.14 show the results of paired t-tests for comparing interpolation methods for multiscalar SPI. Kriging clearly performs better than both IDW 2.5 and IDW 2.0, although the difference between average errors in the methods is not very large as seen in Tables 4.15 and 4.16.

4.1.5. 6-, 9- and 12-month SPEI

The descriptions below refer to Figures 4.17 to 4.20 that show the variation of mean absolute errors for 6-, 9- and 12-month SPEI for January, July and October across the 9 climatic regions. These errors are calculated for USHCN and COOP datasets.

NorthEast

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.40, U=0.44) followed by IDW 2.5 (MAE: C=0.42, U=0.46) and IDW 2 (MAE: C=0.44, U=0.48) and this can be seen for most combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.42, U=0.47) to a minimum of (MAE: C=0.38, U=0.44) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.052, U=0.051) and density of stations (MAE: 0.08). The difference between the two datasets is negligible. The errors are higher (for both datasets) than corresponding values for 1-month SPEI. The variation of errors amongst different month-index combinations is very low.

SouthEast

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.41, U=0.44) followed by IDW 2.5 (MAE: C=0.43, U=0.46) and IDW 2 (MAE: C=0.47, U=0.50) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.44, U=0.50) to a minimum of (MAE: C=0.38, U=0.41) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are:

interpolation method (MAE: C=0.06, U=0.064) and density of stations (MAE: 0.055). The overall difference between the two datasets is also lower as compared to multiscalar SPI and error values for both datasets are similar. The errors are slightly higher (for both datasets) than corresponding values for 1-month SPEI. For USHCN, interpolation accuracy of the multiscalar SPEI is lower than it was for multiscalar SPI.

Central

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.38, U=0.42) followed by IDW 2.5 (MAE: C=0.40, U=0.44) and IDW 2 (MAE: C=0.45, U=0.49) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.40, U=0.43) to a minimum of (MAE: C=0.36, U=0.38).

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.08, U=0.083) and density of stations (MAE: 0.05). The errors are highly similar across all month-index combinations.

EastNorthCentral

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.40, U=0.45) followed by IDW 2.5 (MAE: C=0.43, U=0.50) and IDW 2 (MAE: C=0.48, U=0.55) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.41, U=0.48) to a minimum of (MAE: C=0.36, U=0.41) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.05, U=0.108) and density of stations (MAE: 0.09). Again the variation of errors amongst the month-index combinations is minimal.

South

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.37, U=0.43) followed by IDW 2.5 (MAE: C=0.40, U=0.46) and IDW 2 (MAE: C=0.46, U=0.50) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.39, U=0.48) to a minimum of (MAE: C=0.34, U=0.40) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.05, U=0.075) and density of stations (MAE: 0.08). There is no significant difference in errors between the month-index combinations.

SouthWest

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.43, U=0.50) followed by IDW 2.5 (MAE: C=0.44, U=0.51) and IDW 2 (MAE: C=0.47, U=0.53) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.45, U=0.53) to a minimum of (MAE: C=0.39, U= 0.47) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.05, U=0.056) and density of stations (MAE: 0.11). The difference between USHCN and COOP is lower than it was for multiscalar SPI .The errors are slightly similar to 1-month SPEI for COOP and similar to USHCN. The performance is poor when compared to multiscalar SPI for USHCN.

WestNorthCentral

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.39, U=0.52) followed by IDW 2.5 (MAE: C=0.41, U=0.54) and IDW 2 (MAE: C=0.45, U=0.56) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.40, U=0.55) to a minimum of (MAE: C=0.38, U=0.48) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.06, U=0.033) and density of stations (MAE: 0.16). The seasonal variation of errors is minimal again and the errors are lower than corresponding case for USHCN.

West

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.35, U=0.51) followed by IDW 2.5 (MAE: C=0.37, U=0.52) and IDW 2 (MAE: C=0.39, U=0.54) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.44, U=0.54) to a minimum of (MAE: C=0.31, U=0.45) among the month-index combinations considered..

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.056, U=0.037) and density of stations (MAE: 0.20). The effect of station density on performance is minimal and both datasets perform similarly. The errors are higher (for both datasets) than corresponding values for 1-month SPEI. This region gives the lowest errors amongst the regions considered.

NorthWest

Kriging had the lowest error for 6-, 9- and 12-month SPEI for all months (MAE: C=0.36, U=0.44) followed by IDW 2.5 (MAE: C=0.38, U=0.45) and IDW 2 (MAE: C=0.40, U=0.47) and this can be seen for all combinations in Figures 4.17 and 4.18. The errors vary from a maximum of (MAE: C=0.38, U=0.48) to a minimum of (MAE: C=0.35, U=0.41) among the month-index combinations considered.

The difference between extreme errors (maximum and minimum) are: interpolation method (MAE: C=0.049, U=0.017) and density of stations (MAE: 0.10). COOP performs better than USHCN. The errors are slightly higher (for both datasets) than corresponding values for 1-month SPEI. The performance is not as good as multiscalar SPI for USHCN.

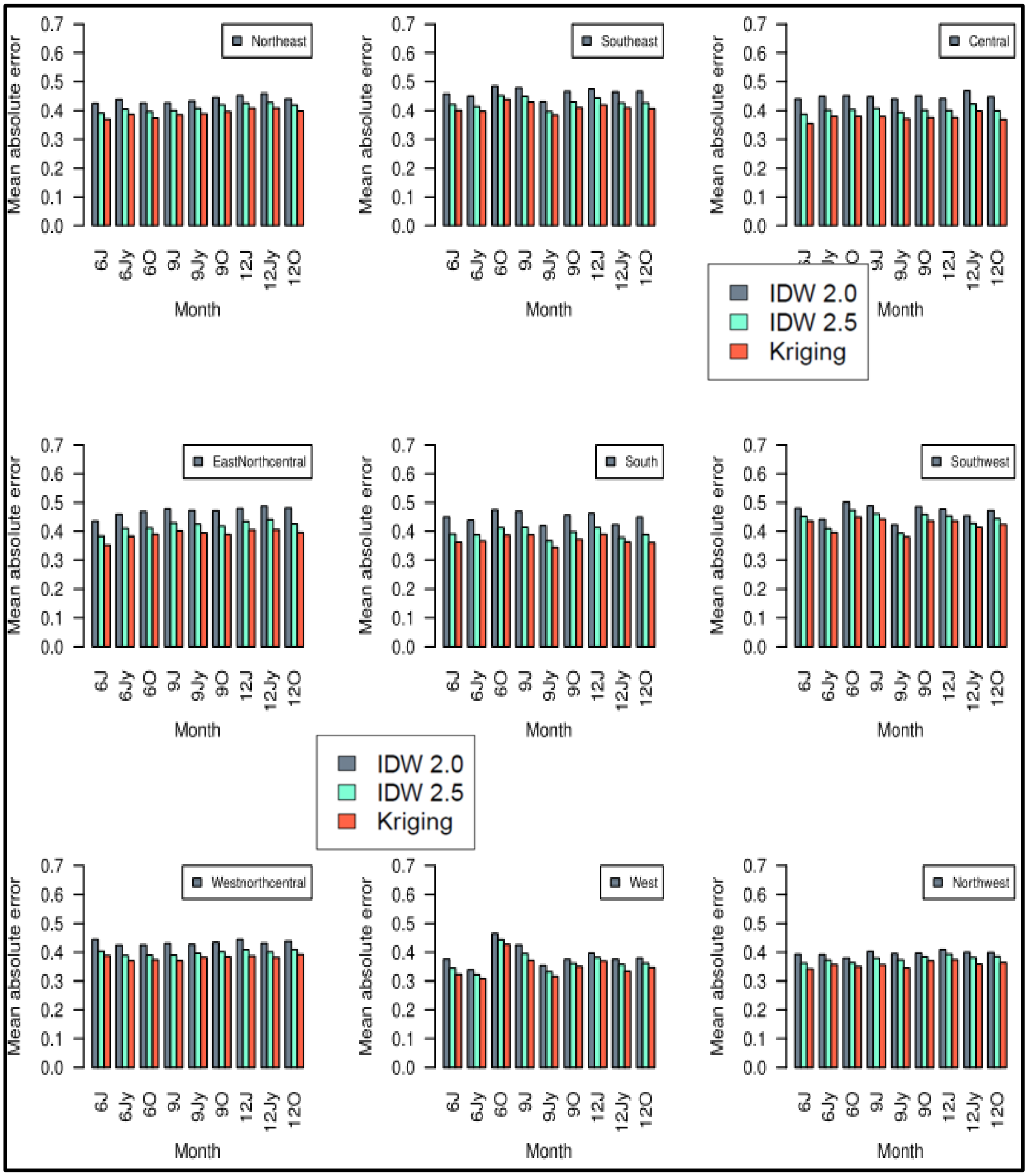

Figure 4.17 Monthly 6-, 9- and 12-month SPEI for 9 climatic regions: COOP network

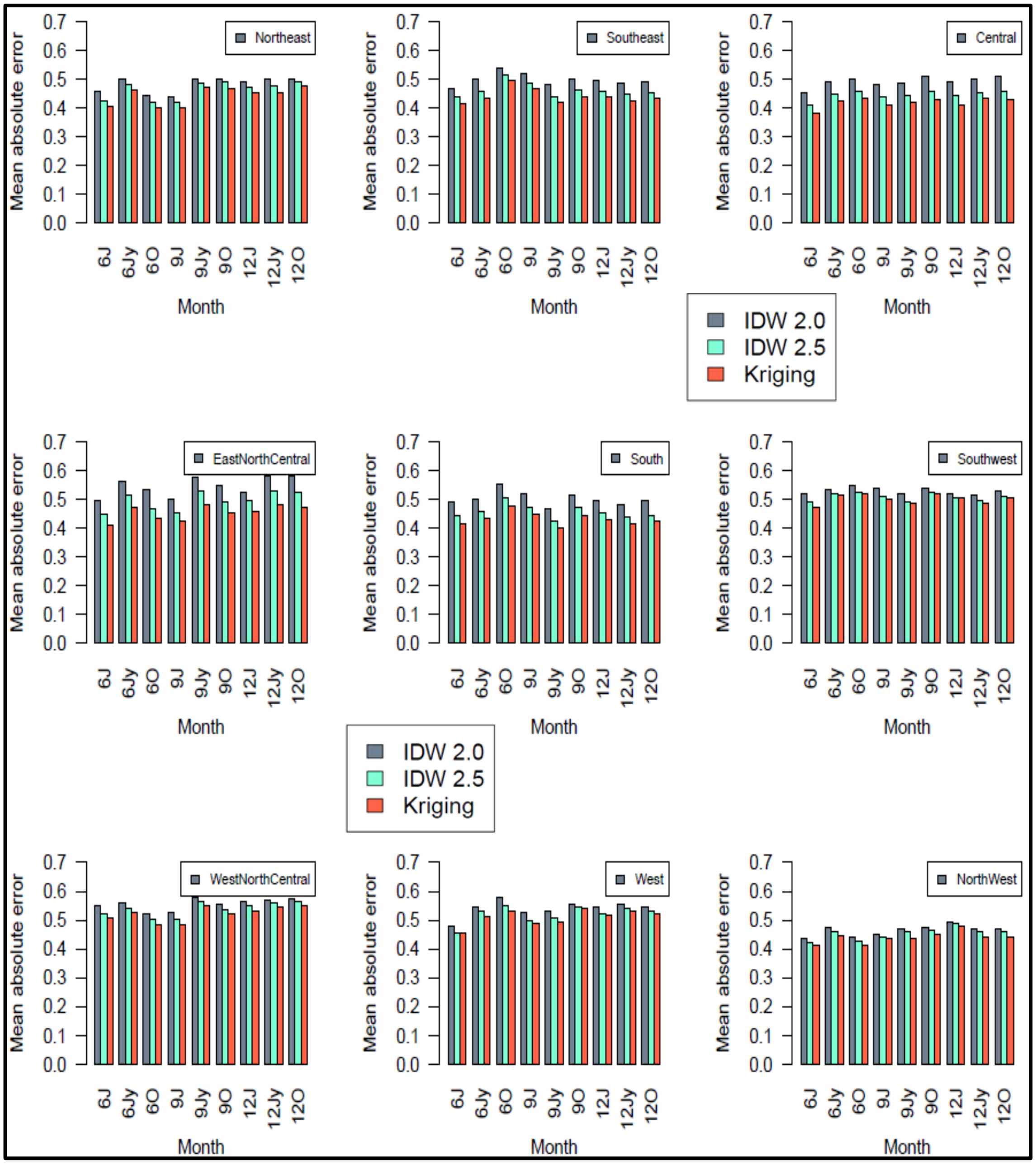

Figure 4.18 Monthly 6-, 9- and 12-month SPEI for 9 climatic regions: USHCN network

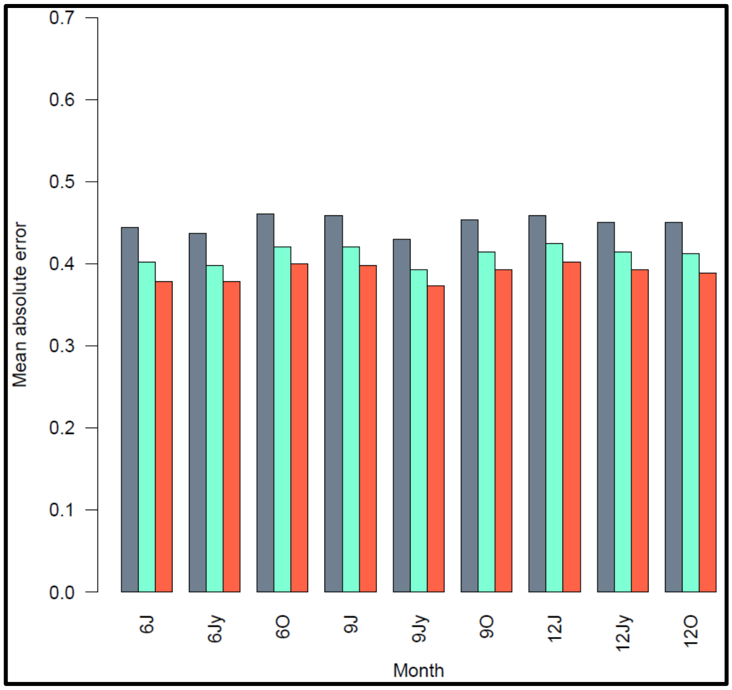

Figure 4.19 6-, 9- and 12-month SPEI for January (J), July (Jy) and October (O) averaged across U.S.: COOP network

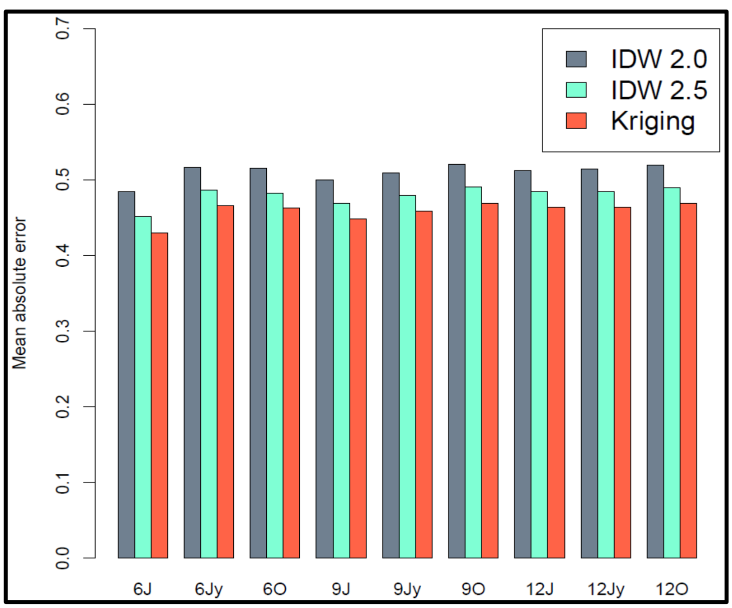

Figure 4.20 6-, 9- and 12-month SPEI for January (J), July (Jy) and October (O) averaged across U.S.: USHCN network

For COOP, the mean absolute errors for multiscalar SPEI are similar to those for multiscalar SPI. The seasonal variation (i.e. month-index combinations) in errors for both datasets is low. More months need to be analyzed to understand the effect of seasonal variations on multiscalar SPEI as well as SPI. The difference between COOP and USHCN is fairly uniform for all regions for multiscalar SPEI as it was for multiscalar SPI and this is confirmed in Figures 4.19 and 4.20. The multiscalar SPEI uses both precipitation and temperature values. Temperature, which improved the spatial performance of 1-month SPEI over SPI, seems to have a similar effect on the longer scales and hence the accuracy of the interpolated multiscalar SPEI is slightly better than multiscalar SPI.

The variation of errors across climatic regions is quite low for multiscalar SPEI in spite of the differing station densities. This is similar to the performance of 1-month SPEI which showed consistent spatial performance across datasets, climatic regions and seasons. For COOP the West and South climatic regions have lower errors than other regions.

Table 4.17 Summary of paired t-tests for multiscalar SPEI, 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.0

Result	**Number of occurrences**	
	COOP	**USHCN**
1 Kriging performs better than IDW 2.0 at 90% confidence level	72	78
2 IDW 2.0 performs better than Kriging at 90% confidence level	0	0
3 There is no statistically significant difference between the two methods at 90% confidence level	9	3

Table 4.18 Summary of paired t-tests for multiscalar SPEI, 9 climatic regions * 3 months = 27 combinations, Kriging versus IDW 2.5

Result	**Number of occurrences**	
	COOP	**USHCN**
1 Kriging performs better than IDW 2.5 at 90% confidence level	53	65
2 IDW 2.5 performs better than Kriging at 90% confidence level	5	0
3 There is no statistically significant difference between the two methods at 90% confidence level	23	16

Table 4.19 Multiscalar SPEI, Mean absolute errors, COOP

	Kriging	IDW 2.0	IDW 2.5
Mean	0.39	0.45	0.42
Median	0.33	0.39	0.36

Table 4.20 Multiscalar SPEI, Mean absolute errors, USHCN

	Kriging	IDW 2.0	IDW 2.5
Mean	0.45	0.51	0.48
Median	0.36	0.42	0.39

Tables 4.17 and 4.18 show the results of comparison of interpolation methods for all instances made using paired t-tests. It can clearly be seen that kriging performs significantly better than IDW 2.5 and IDW 2.0 in most cases. However Tables 4.19 and 4.20 reiterate that there are differences in mean absolute errors between the three interpolation methods.

4.2. Comparison of Drought Indices

The normalized errors were used to enable three comparisons between interpolation errors of drought indices using paired t-tests over climatic regions for both USHCN and COOP datasets.

4.2.1 Comparison of 1-month SPI and 1-month SPEI

The difference of absolute errors between interpolation of 1-month SPI and 1-month SPEI for every instance is compared using a paired t-test. This is done over 9 climatic regions and 3 months (January, July and October) and the results are summarized here. This approach helps to compare the relative performance of the indices under different conditions.

Table 4.21 Paired t-tests, 1-month SPI versus 1-month SPEI, 9 climatic regions and 3 months

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Interpolation of 1-month SPI performs better than interpolation of 1-month SPEI 1 at 90% confidence level	6	4
2 Interpolation of 1-month SPEI performs better than interpolation of 1-month SPI at 90% confidence level	4	6
3 There is no statistically significant difference between the interpolation of two indices at 90% confidence level	17	17

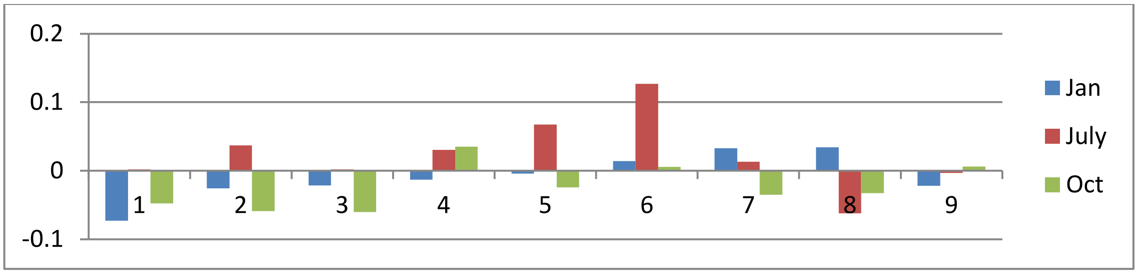

Figure 4.21 Difference of normalized interpolation errors for 1-month SPI and 1-month SPEI for 9 climatic regions: COOP

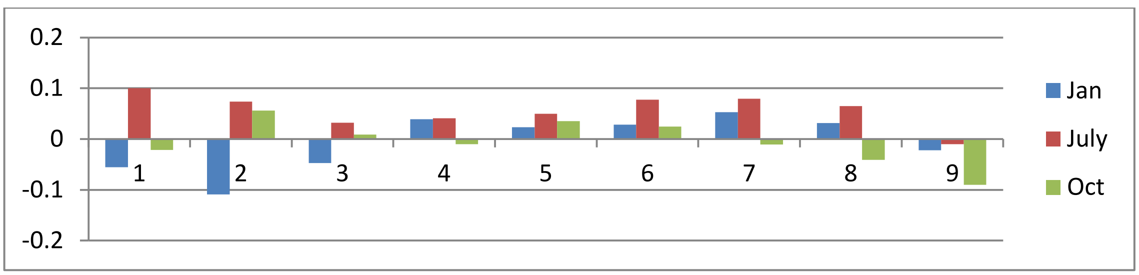

Figure 4.22 Difference of normalized errors for 1-month SPI and 1-month SPEI for 9 climatic regions: USHCN

Table 4.21 suggests that there is not a significant difference in the performance of both methods based on a comparison of normalized errors. There are some variations over climatic regions. Interpolation of SPEI performs better than interpolation of SPI in regions 4 to 7 (central U.S.), however the magnitude of these differences is low. In Section 4.1 it was seen that interpolation of 1-month SPEI performed slightly better than interpolation of 1-month SPI for many cases. The difference between the errors of the two drought indices is very low (less than 0.1 in almost all of the cases).

4.2.2 Comparison of 9-month SPI and PDSI

The difference between absolute errors (normalized values) of interpolation of 9-month SPI and PDSI for every instance is compared using paired t-tests. Table 4.22 shows that the normalized errors for interpolation of PDSI are lower than those for interpolation of 9-month SPI for almost all cases when COOP is considered. However, the opposite is true for USHCN. The higher station density of COOP appears to be more suitable for PDSI, whereas the longer time series of USHCN gives more accurate results for calculating multiscalar SPI as seen in Figures 4.23 and 4.24.

Table 4.22 Paired t-tests, 9-month SPI versus PDSI, 9 climatic regions and 3 months

	Number of occurrences	
Result	**COOP**	**USHCN**
1 Interpolation of 9-month SPI performs better than interpolation of PDSI at 90% confidence level	0	10
2 Interpolation of PDSI performs better than interpolation of 9-month SPI at 90% confidence level	25	0
3 There is no statistically significant difference between the interpolation of two indices at 90% confidence level	2	17

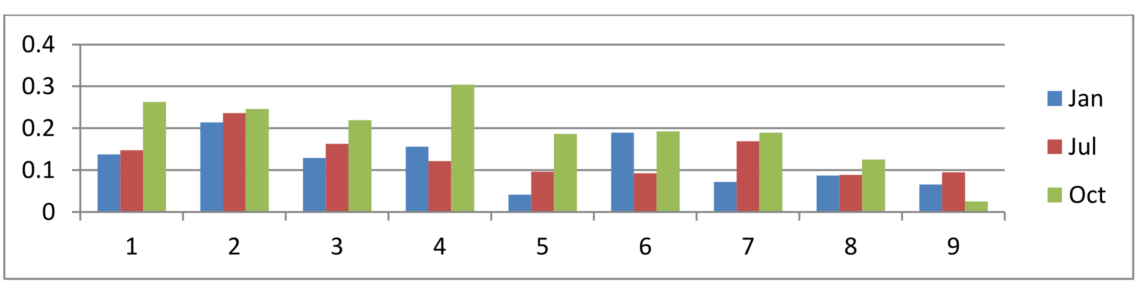

Figure 4.23 Difference of normalized errors over 9 climatic regions, 9-month SPI - PDSI, COOP network

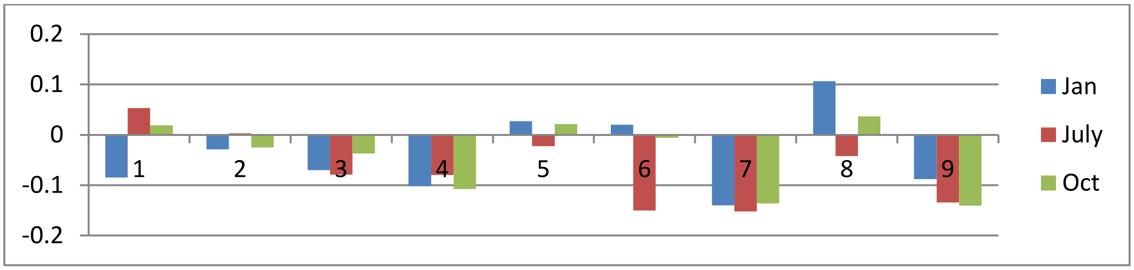

Figure 4.24 Difference of normalized errors over 9 climatic regions, 9-month SPI - PDSI, USHCN network

4.2.3. Comparison of 9-month SPEI and PDSI

The difference between absolute errors (normalized values) between 9-month SPEI and PDSI for every instance is compared using a paired t-test. The results in this case are similar to the comparison of 9-month SPI and PDSI. Table 4.23 shows that COOP is more accurate for interpolation of PDSI. For USHCN there is no significant difference in the performance with the PDSI and SPEI. PDSI and SPEI both consider precipitation and temperature data in their calculations. In the evaluation of performance of SPEI (Section 4.1.2) it was observed that interpolation of multiscalar SPEI performed worse than 1-month SPEI and multiscalar SPI.

Table 4.23 Paired t-tests, 9-month SPEI versus PDSI: 9 climatic regions and 3 months

Result	Number of occurrences	
	COOP	USHCN
1 Interpolation of 9-month SPEI performs better than interpolation of PDSI at 90% confidence level	0	3
2 Interpolation of PDSI performs better than interpolation of 9-month SPEI at 90% confidence level	26	3
3 There is no statistically significant difference between the two indices at 90% confidence level	1	21

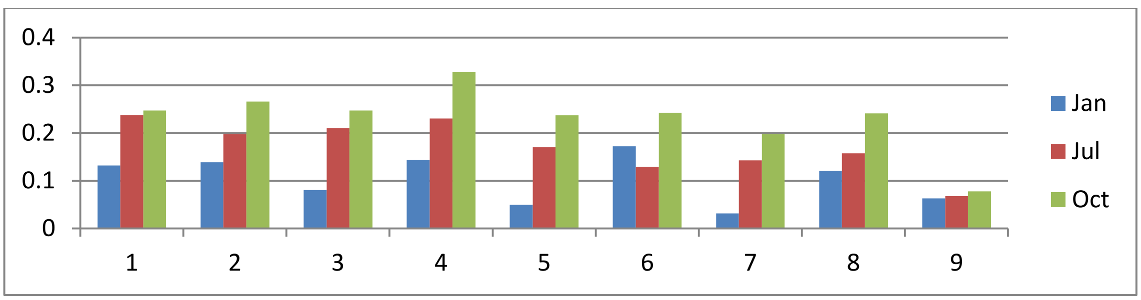

Figure 4.25 Difference of normalized errors for 9 climatic regions, 9-month SPEI - PDSI, COOP network

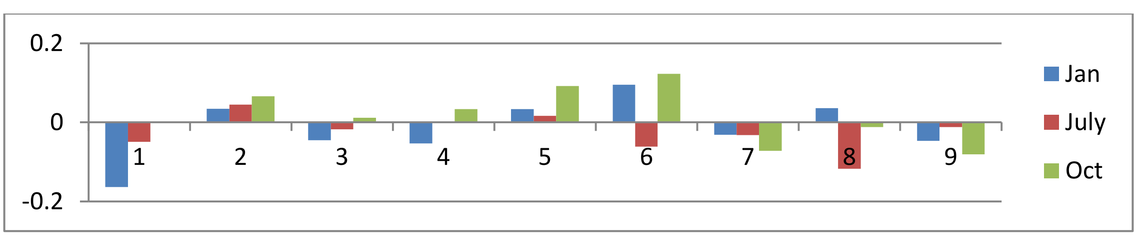

Figure 4.26 Difference of normalized errors for 9 climatic regions, 9-month SPEI - PDSI, USHCN network

4.3. Comparison of Months (Seasonality)

4.3.1. January and July

Paired t-tests were used to compare the relative performance of the same drought index in January and July for a number of instances. Table 4.24 shows the results of Wilcoxon tests and Figures 4.27 and 4.28 shows the variation of relative performance of the 5 drought indices over the 9 climatic regions.

Table 4.24 Paired t-test for January versus July: 3 drought indices and 9 climatic regions

Result	**Number of occurrences**	
	COOP	**USHCN**
1 Interpolation in January performs better than July at 90% confidence level	21	19
2 Interpolation in July performs better than January at 90% confidence level	0	0
3 There is no statistically significant difference between the two months at 90% confidence level	6	8

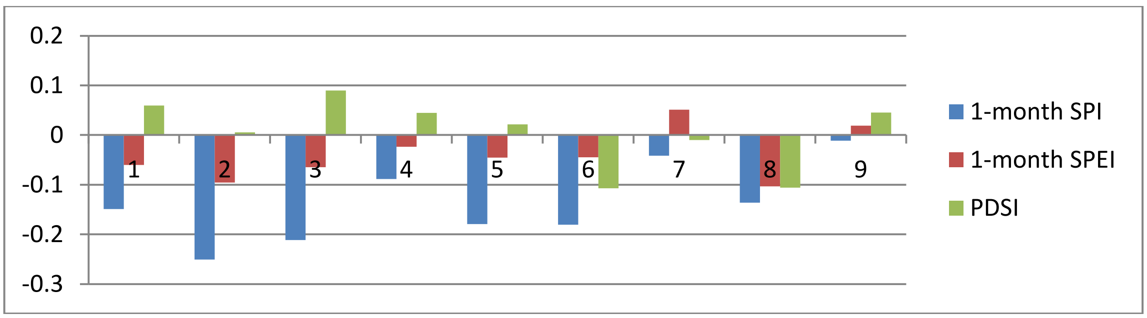

Figure 4.27 Difference of mean absolute errors for 3 indices, January - July over 9 climatic regions, COOP network

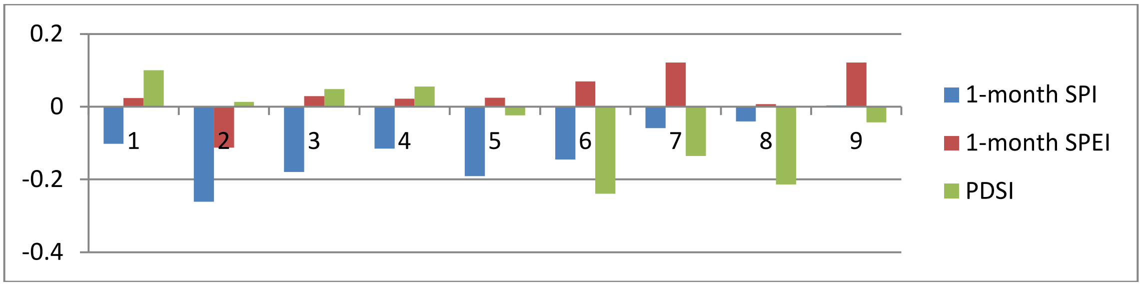

Figure 4.28 Difference of mean absolute errors for 3 indices, January - July over 9 climatic regions, USHCN network

There is significant statistical evidence (Table 4.24) that the performance of drought indices across climatic regions is better in January (winter) than July. This difference is accentuated by regional climatic patterns.

In Section 4.1 it was observed that precipitation patterns (and hence seasonality) were the most significant factor affecting spatial accuracy of 1-month SPI and SPEI. This is clearly reiterated in Figures 4.27 and 4.28 that show the difference of errors for January (winter) and July (summer) for the 3 drought indices over 9 climatic regions. The most significant difference is clearly seen for 1-month SPI and 1-month SPEI for all climatic regions except in the Northwest and West. The difference of seasonal errors is not consistent for PDSI, it varies significantly by climatic region as well as dataset. As observed in Section 4.1.3 PDSI had a lower overall variation which is attributed to the fact that it considers a longer-term moisture signal. It is difficult to make broader conclusions about the performance of PDSI from this figure and conclusions for individual cases would be more useful.

4.3.2. July and October

Paired t-tests were used to compare the relative performance of three drought indices in July and October. Table 4.25 shows the results of paired t-tests and Figures 4.29 and 4.30 shows the variation in relative performance of the 3 drought indices over 9 climatic regions.

Table 4.25 Paired t-test of July versus October: 3 drought indices and 9 climatic regions

Result	Number of occurrences	
	COOP	USHCN
1 Interpolation in July performs better than October at 90% confidence level	2	3
2 Interpolation in October performs better than July at 90% confidence level	22	19
3 There is no statistically significant difference between the two months at 90% confidence level	3	5

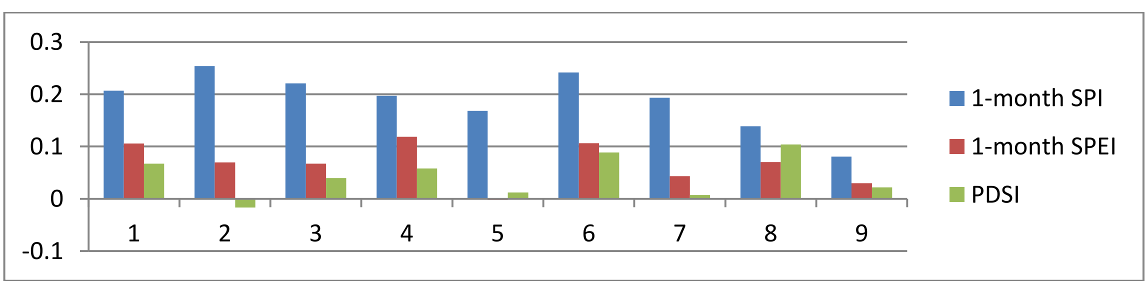

Figure 4.29 Differences of errors for the 3 indices in July versus October over 9 climatic regions, COOP network

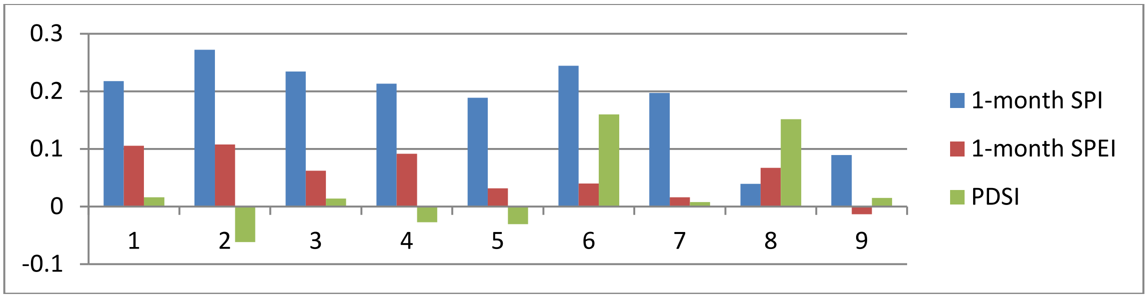

Figure 4.30 Differences of errors for the 3 drought indices in July versus October over 9 climatic regions, USHCN network

There is significant statistical evidence (Table 4.25) to show that the errors across indices and climatic regions are higher for July when compared to October. As in the previous case, the largest differences are observed for 1-month SPI followed by 1-month SPEI. PDSI shows relatively small differences. Multiscalar SPI and SPEI have larger differences for COOP than for USHCN.

The above statistical tests when combined with observations in the Sections 4.1 and the figures in Section 4.4, suggest that the accuracy of drought index interpolations are lower during the summer months.

4.4. Examination of Spatial Variation in Interpolation Error

The comparisons of interpolation accuracy across climatic regions so far involved averaging the cross-validation errors for all stations within each of the 9 climatic regions. It is important to examine not just the average error, but also the spatial distribution of error within each climatic region. This is important because the density of stations varies substantially within the climatic regions. The climatic regions used for comparison are very large and localized clusters of higher or lower errors for certain months and drought indices are more helpful to understand drought maps.

The spatial variation of mean absolute errors is examined by interpolating the errors to a grid over the U.S. for January and July (for 1-month SPI, 1-month SPEI and PDSI) using IDW 2.5. The spatial distribution of errors is then explained by referencing the results in Section 4.1. Only two months are considered because they are observed to represent the extreme cases (high and low errors based on seasonality) as determined in Sections 4.1 and 4.2. The legend categories are the same for the SPI and SPEI, and have been modified for PDSI to accommodate its higher values.

4.4.1 1-month SPI, January

Figures 4.31 and 4.32 show the variation of mean absolute errors over the continental U.S. for 1-month SPI. Figure 4.33 shows that the mean absolute error varies from 0.26 in the Central region to 0.43 in the West North Central region (COOP) and corresponding values for USHCN are 0.31 to 0.49. The errors for COOP are lower than USHCN values for each region.

The Central region has the highest density of COOP stations amongst all climatic regions (6.45 stations per 10,000 km^2) as well as the highest density of USHCN stations (2.07 stations per 10,000 km^2). In comparison the station density for West North Central region is 4.51 per 10,000 km^2 for COOP and 1.38 per 10,000 km^2 for USHCN. The mountainous terrain and lower station density result in higher interpolation errors in the West North Central region.

The West climatic region has the lowest station density amongst all regions (3.27 stations per 10,000 km^2 for COOP and 0.87 stations per 10,000 km^2 for USHCN), but it also has very low interpolation error (COOP = 0.27 and USHCN = 0.37). January is the month with highest precipitation in the West climatic region. This is an example of how, although higher station density can help improve interpolation accuracy, the precipitation pattern is the most significant factor that controls the interpolation accuracy for 1-month SPI.

The two figures show that the majority of the U.S. (except for the mountainous western U.S.) has errors that range from 0.2 to 0.4. Very few locations have errors less than 0.2 or greater than 0.8. Florida is one of the locations where the more dense COOP network significantly improves the interpolation accuracy.

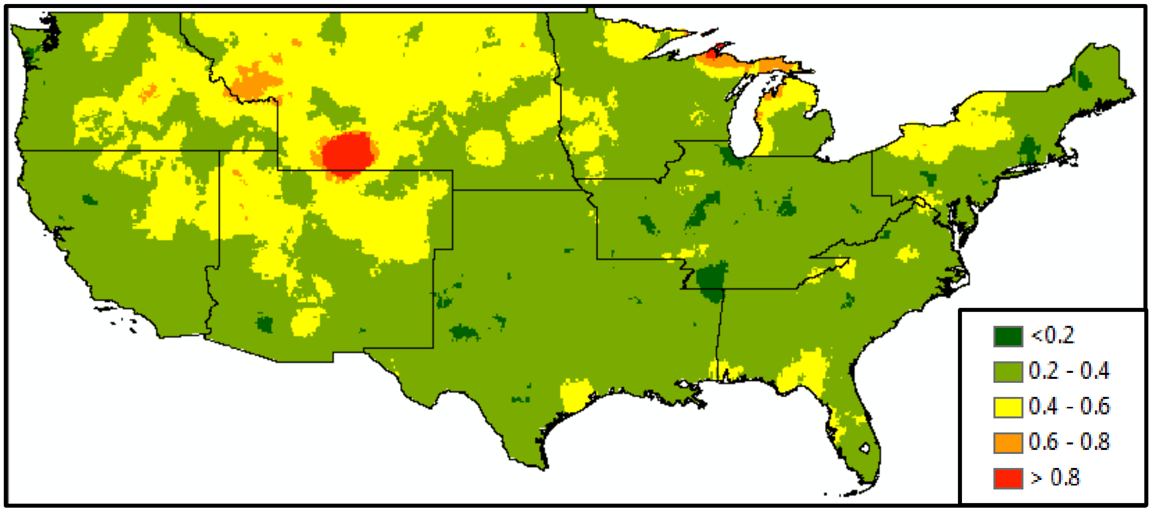

Figure 4.31 Mean absolute error for 1-month SPI, January, COOP network

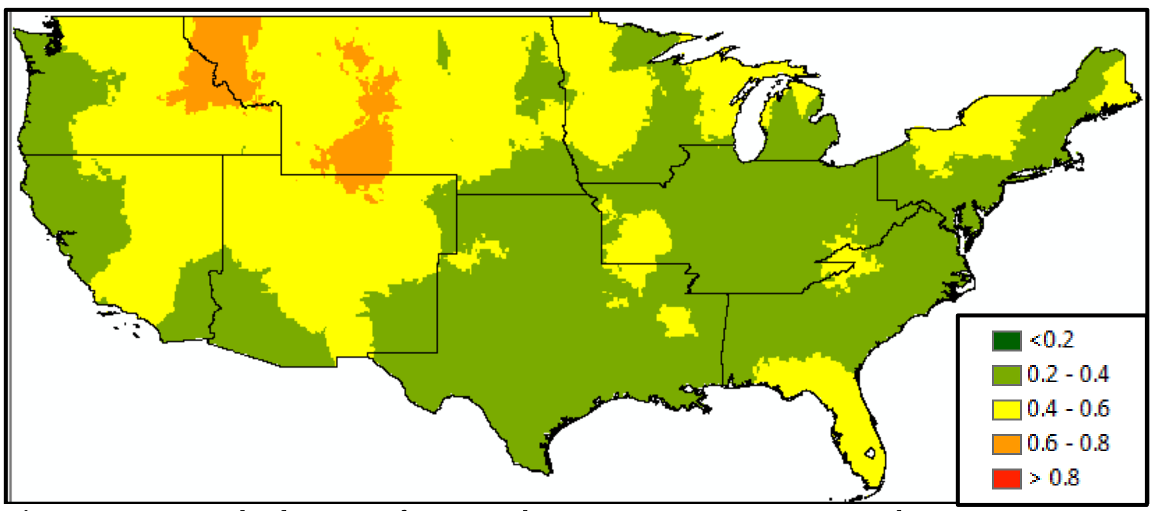

Figure 4.32 Mean absolute error for 1-month SPI, January, USHCN network

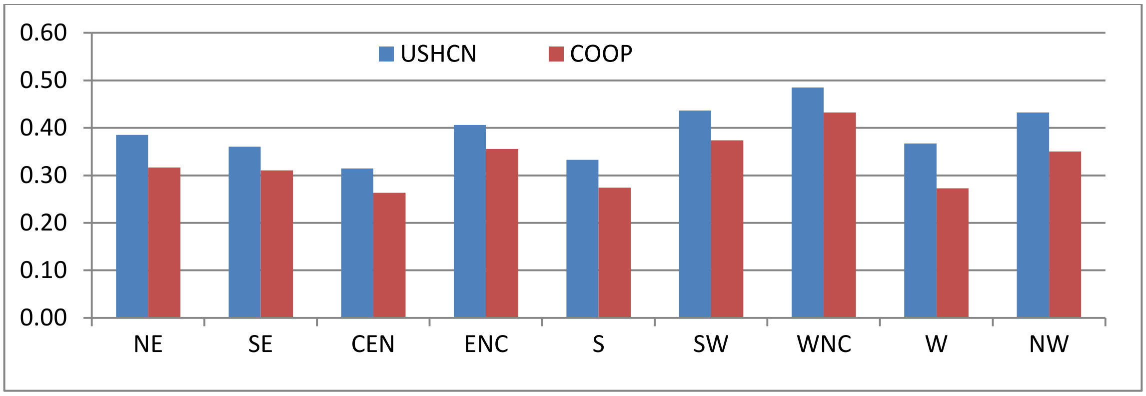

Figure 4.33 Mean absolute errors for 1-month SPI, January, 9 climatic regions

4.4.2 1-month SPI, July

Figures 4.34 and 4.35 show the variation of mean absolute errors in July for 1-month SPI. The evaluation of errors for 1-month SPI in Section 4.1.1 demonstrated that precipitation climatology associated with seasonality has the greatest influence on interpolation accuracy. Therefore, in almost all regions, the accuracy in July is lower than other months. This can be clearly seen by comparing Figure 4.34 and 4.35 to 4.31 and 4.32. The errors across most of the U.S. are higher in July than in January. Figure 3.8 shows that the highest error is seen in the Southeast, Southwest and Westnorthcentral regions.

The lowest interpolation errors are found in the West and Northwest, where July precipitation is low. Errors across most of U.S. vary from 0.4 to 0.6, with lower errors for COOP in the Central Great Plains. Higher errors occur in the mountainous western U.S., as well as in Florida, due to the prevalence of convective precipitation.

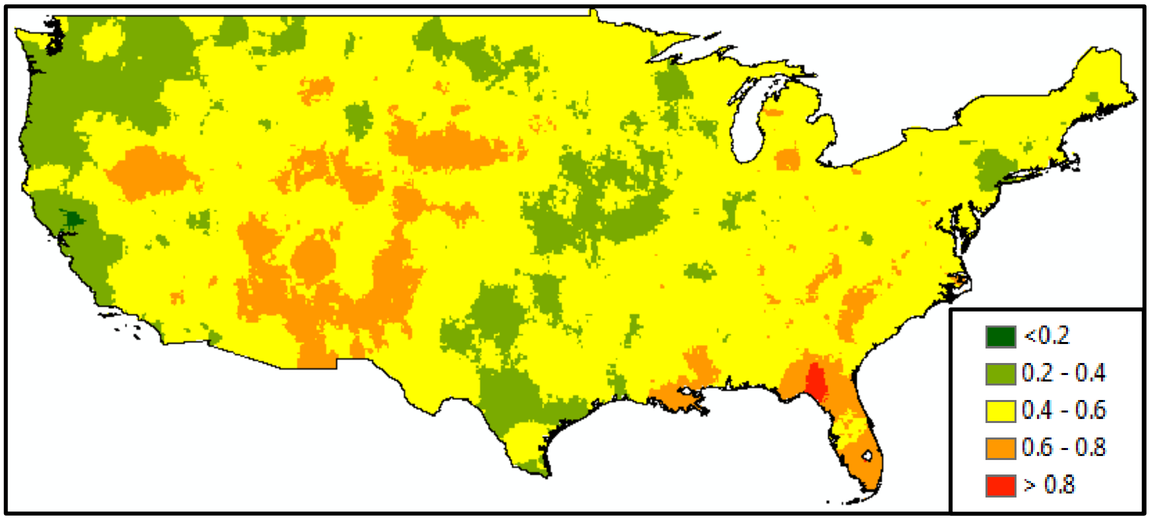

Figure 4.34 Mean absolute error for 1-month SPI, July, COOP network

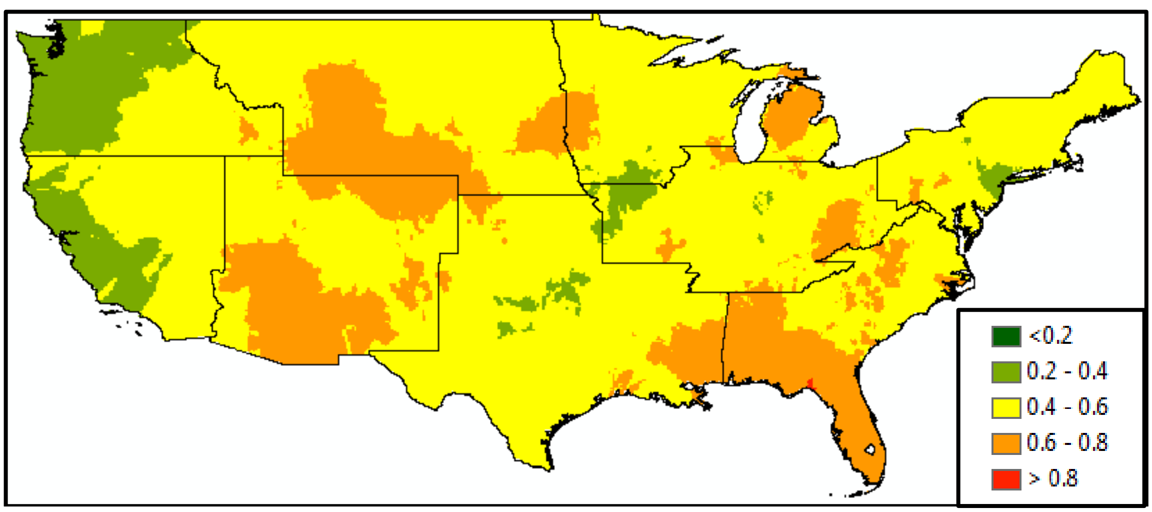

Figure 4.35 Mean absolute error for 1-month SPI, July, USHCN network

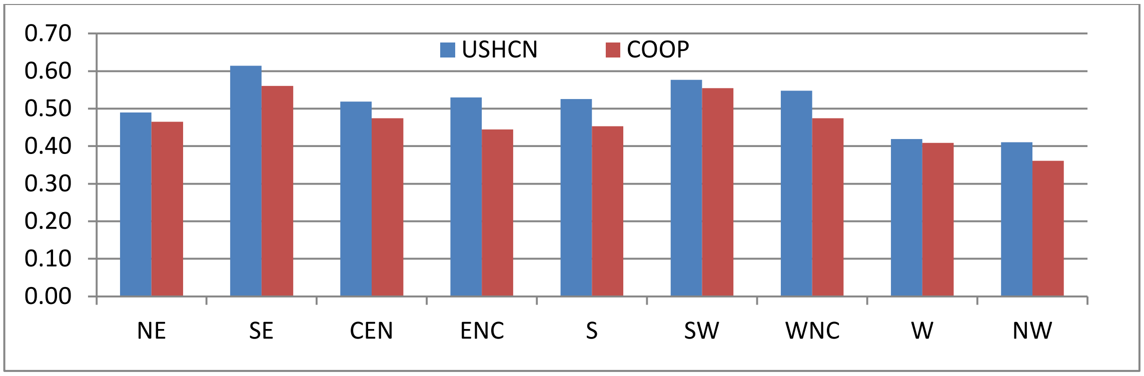

Figure 4.36 Mean absolute error for 1-month SPI, July, 9 climatic regions

4.4.3 1-month SPEI, January

Figures 4.37 and 4.38 show the variation of 1-month SPEI for the month of January across USA. In Section 4.1 it was demonstrated that 1-month SPEI interpolation errors were slightly lower than 1-month SPI. However as shown in Section 4.2, these differences are not statistically significant. The differences between 1-month SPI and 1-month SPEI for January are minimal. The pattern of mean absolute errors for 1-month SPEI for both COOP and USHCN is quite similar to that of the 1-month SPI. The mean absolute errors varied from 0.2 to 0.4. COOP is more accurate in mountainous regions for 1-month SPEI, as compared to 1-month SPI, especially in the West North Central region. Figure 4.39 shows that the highest errors occur in Southwest and Westnorthcentral regions. The difference in performance of two datasets can also be seen for all regions.

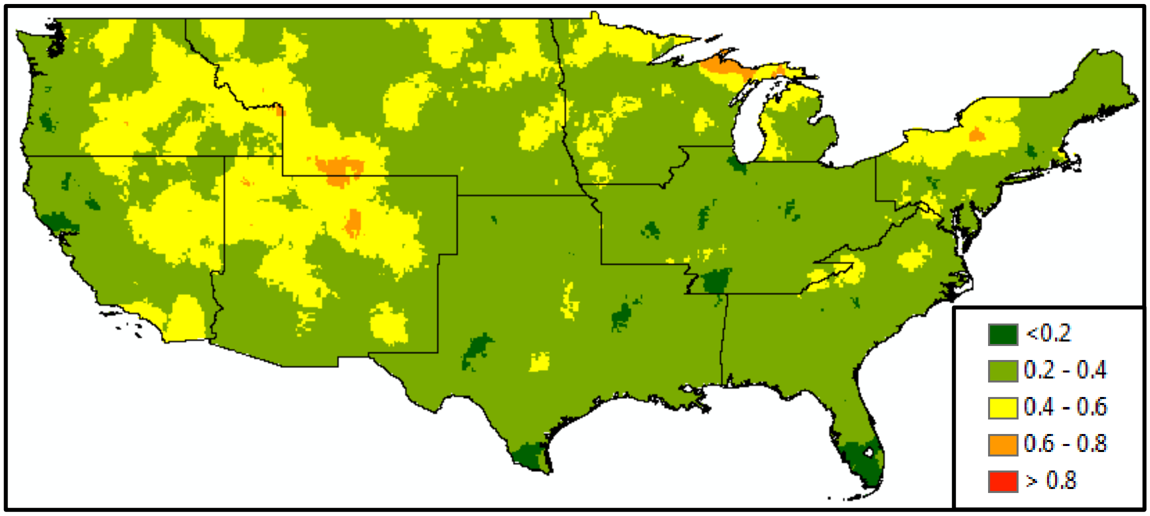

Figure 4.37 Mean absolute error for 1-month SPEI, January, COOP network

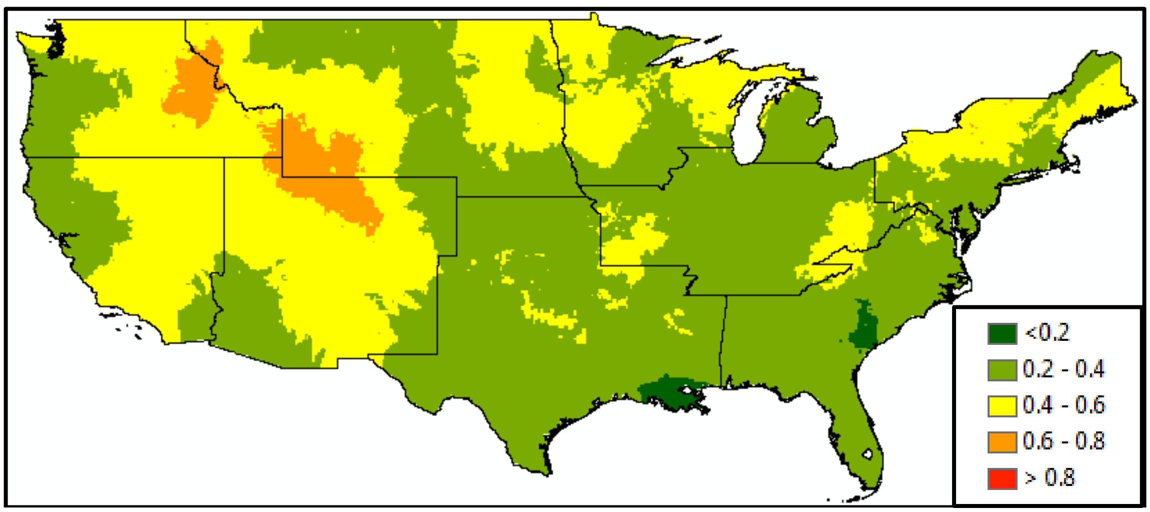

Figure 4.38 Mean absolute error for 1-month SPEI, January, USHCN network

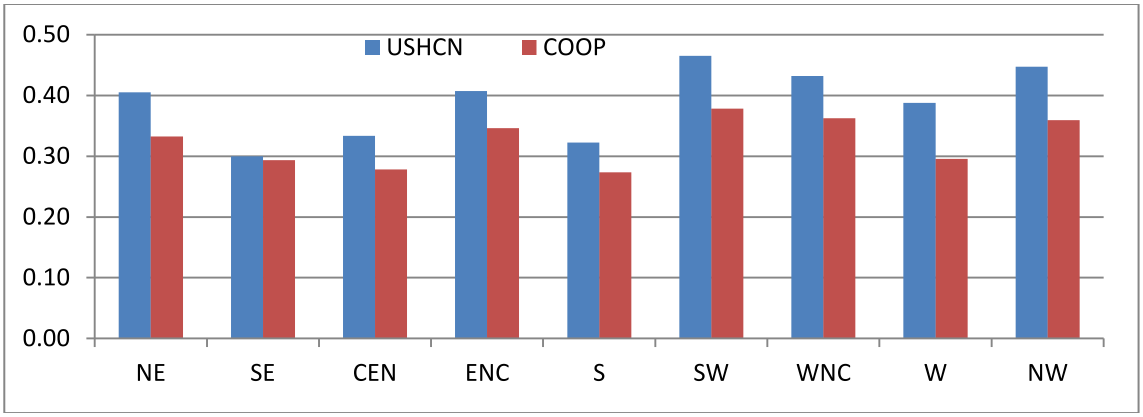

Figure 4.39 Mean absolute errors for 1-month SPEI, January, 9 climatic regions

4.4.4 1-month SPEI, July

The accuracy of 1-month SPEI is greater than the accuracy of 1-month SPI in July. This is because precipitation during the summer is primarily due to convection and therefore it is highly spatially heterogeneous. This effect is seen for both COOP and USHCN datasets. Although COOP performs better than USHCN for 1-month SPEI, the difference between the datasets is not statistically significant as seen in Section 4.1. This suggests that the use of temperature in the SPEI produces a drought index that is more spatially consistent. Figure 4.40 and 4.41 show the variation of errors for 1 month SPEI and highest errors can be seen over Southeast as well as Southwest USA. The COOP datasets more localized variation as compared to USHCN due to the higher density of stations. Figure 4.42 shows higher errors in Southeast, Northeast and Southwest USA. The relative errors between USHCN and COOP are quite similar.

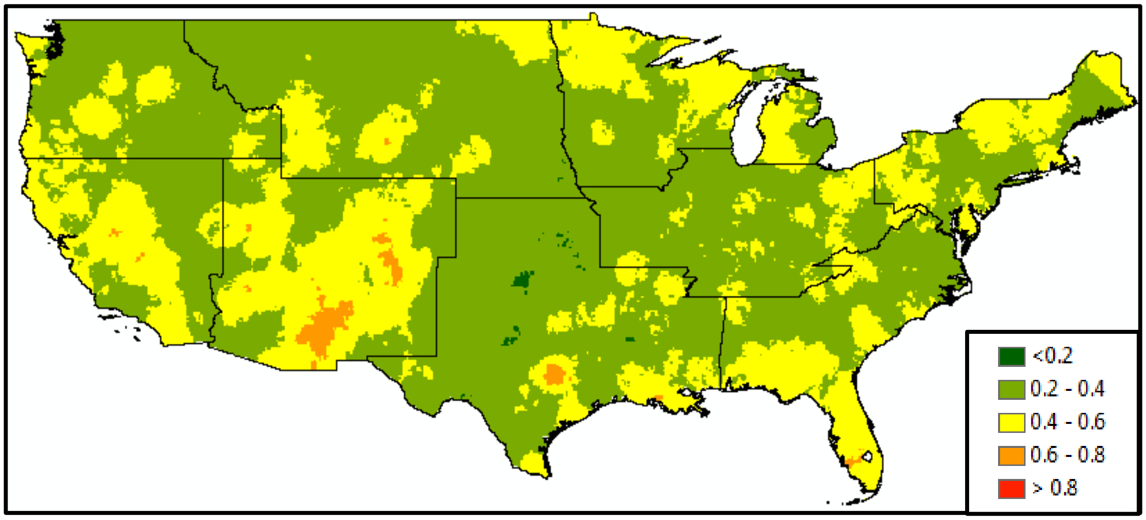

Figure 4.40 Mean absolute error for 1-month SPEI, July, COOP network

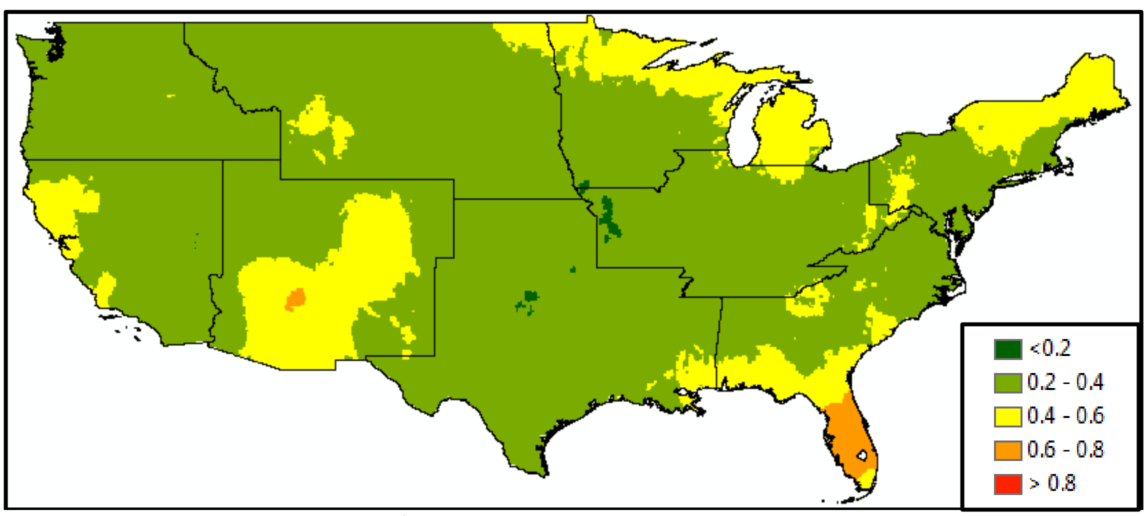

Figure 4.41 Mean absolute error for 1-month SPEI, July, USHCN network

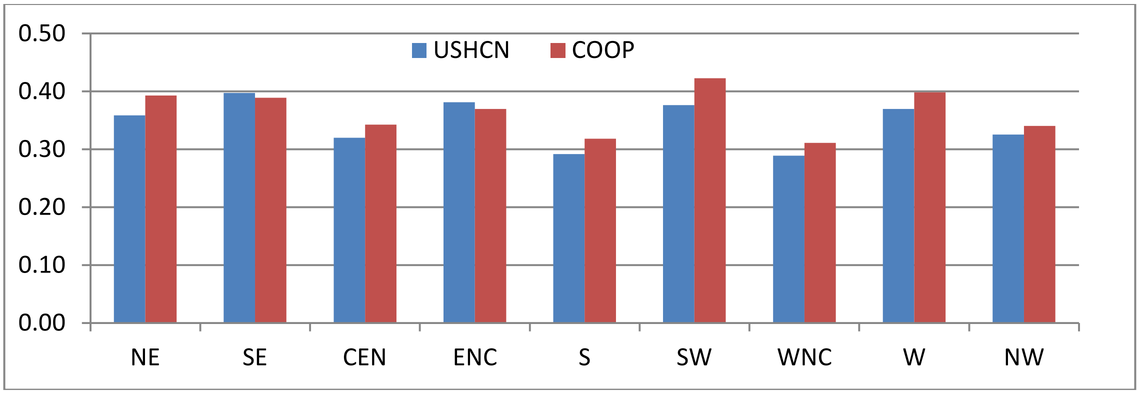

Figure 4.42 Mean absolute errors for 1-month SPEI, July over 9 climatic regions

4.4.5. PDSI, January

The results show that interpolation errors for COOP were smaller than the errors for USHCN (Figure 4.45). The errors for COOP vary from 0.8 in the West to 1.04 in the Northeast. The corresponding values for USHCN vary from 0.97 in the West to 1.18 in the Southeast (1.16 for Northeast). The use of the higher density COOP network results in improved interpolation accuracy. The mean absolute errors for most of the country are less than 1.2. Although the differences of overall interpolation errors for ordinary kriging between USHCN and COOP are not very large, the spatial patterns are significantly different. The lowest errors for USHCN occur in the Central Great Plains for both datasets. The errors are highest in Southeast. Figure 4.44 shows the variation for USHCN datasets and clearly large areas with higher errors are seen for this case, the best performance can be observed over the central United States. The COOP errors although slightly lower than USHCN for all regions as seen in Figure 4.43 show highly localized patterns of errors across the U.S. This is unlike the maps observed for SPI and SPEI.

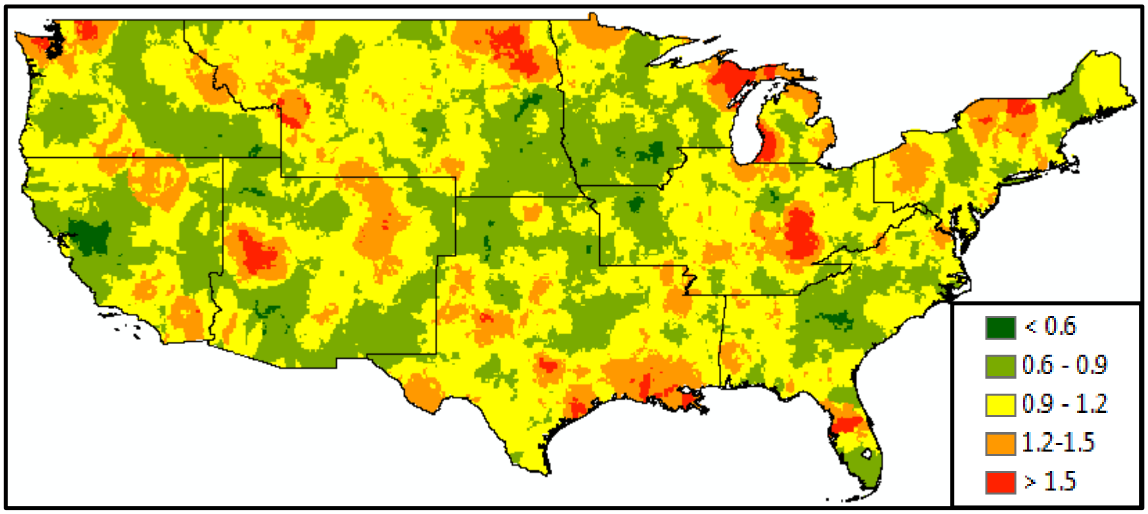

Figure 4.43 Mean absolute error for PDSI, January, COOP network

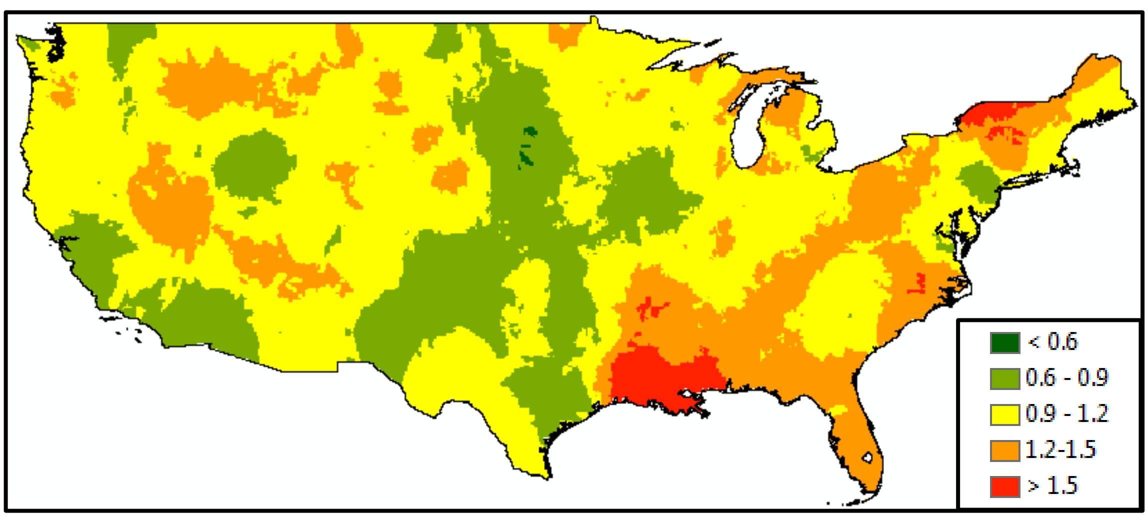

Figure 4.44 Mean absolute error for PDSI, January, USHCN network

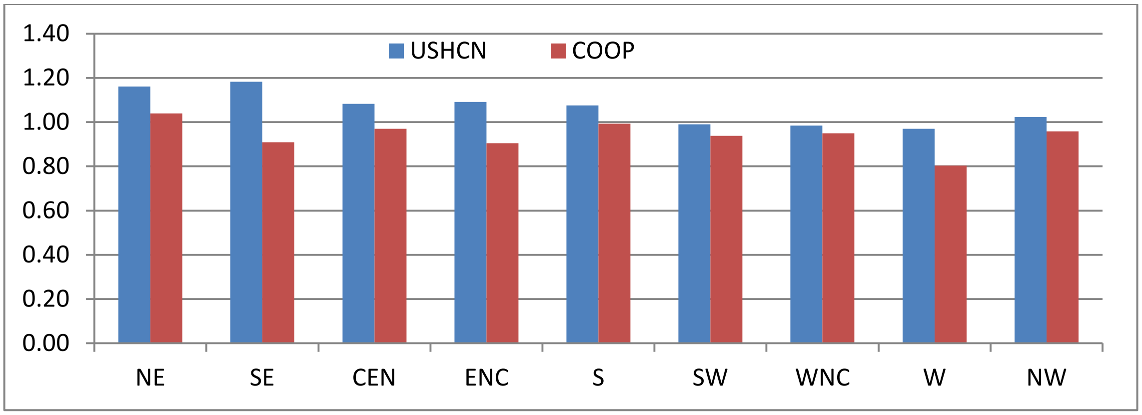

Figure 4.45 PDSI, January, mean absolute errors over 9 climatic regions

4.4.6. PDSI, July

Figures 4.46 and 4.48 show the variations in PDSI interpolation error in July. The seasonal variation of PDSI, as mentioned previously, is lower that for the SPI and so the July error map is similar to the January error map. The errors for COOP vary from 0.86 in the EastNorthCentral (0.88 for the Central region) to 1.05 in the Southwest. The corresponding values for USHCN are 1.02 for the Central region and 1.25 for the Southwest. The variation of errors across climatic regions is consistent across both the datasets for both January and July. This was also observed in Section 4.1. The higher station density of the COOP network causes many local patterns that are not produced by USHCN. Figure 4.47 for USHCN show the higher amount of errors for PDSI in the month of July as compared to January. Although the errors for COOP are lower for all cases when compared to USHCN the spatial patterns for COOP are very localized. This can be seen from Figure 4.46 where it can be observed that for some small areas the errors in COOP are significantly lower than USHCN.

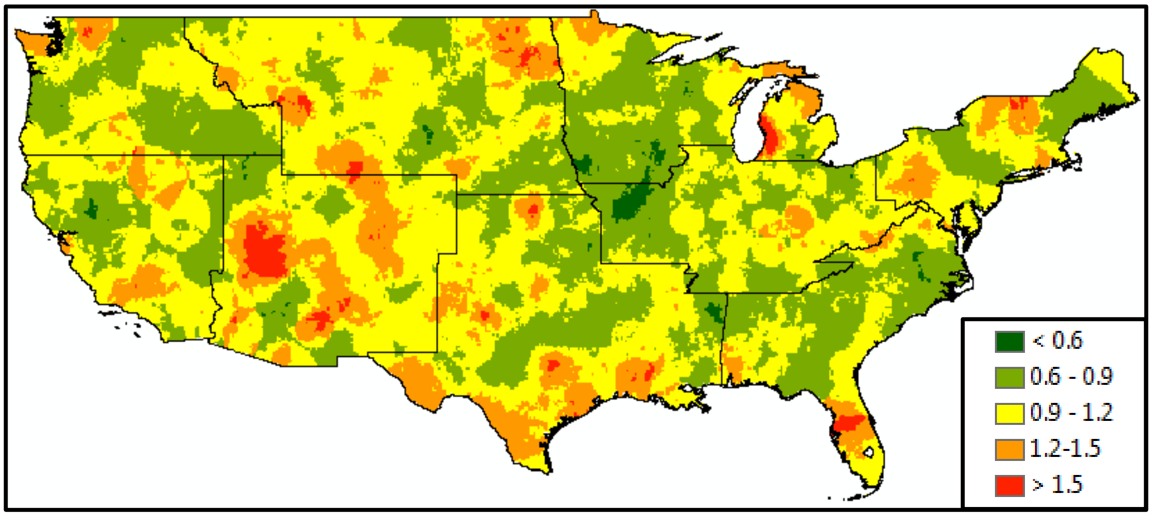

Figure 4.46 Mean absolute error for PDSI, July, COOP network

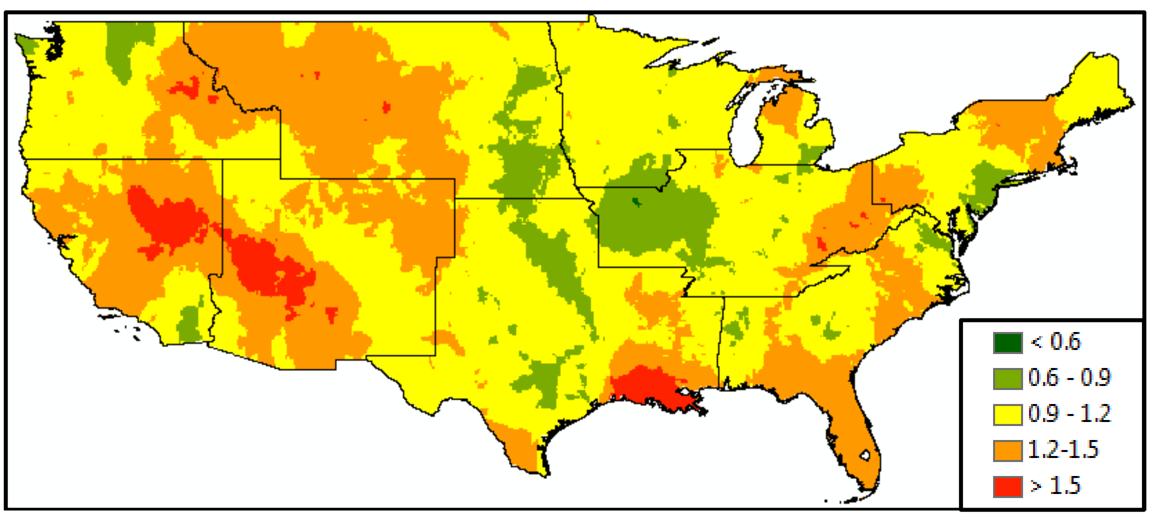

Figure 4.47 Mean absolute error for PDSI, July, USHCN network

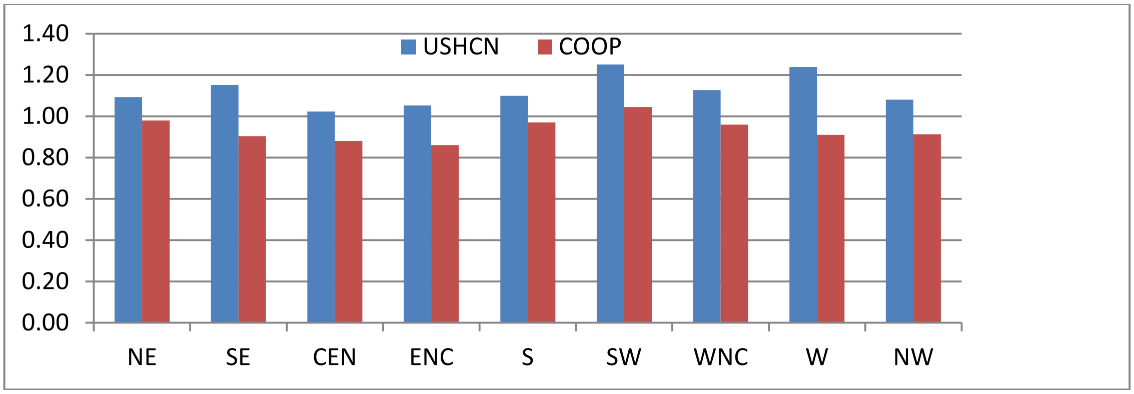

Figure 4.48 PDSI, July, mean absolute errors over 9 climatic regions

4.5 Limitations of This Study

There are a number of limitations in the methodological approach used in this thesis and they include:

1. Only three months are compared statistically to understand influence of seasonality in Section 4.1. To clearly delineate the influence of seasonality by months more individual statistical comparisons are required.

2. The comparison of drought indices was only undertaken for specific cases that were thought to be equivalent. For example, the 9-month SPI was compared to the PDSI using normalized errors. More comparisons are necessary to understand the influence of inherent nature of moisture indices. For example, additional comparisons could examine the relationship between 6- and 12-month SPI/SPEI and PDSI.

3. The influence of climatic regions on interpolation accuracy were assessed using only two months. This was done for practical reasons, however this may result in

the analysis overlooking how seasonal variations in precipitation patterns influence interpolation accuracy.

4. Multiscalar indices (e.g., 6-, 9- and 12-month SPI and SPEI) were examined only for January, July and October. Seasonality was found to be the most significant factor influencing interpolation accuracy for 1-month SPI and SPEI and therefore we expect that if all 12 months had been examined it would allow us to draw a similar conclusion for multiscalar SPI/SPEI.

5. The gamma distribution was used for calculating the SPI and SPEI at all locations so that they are comparable. However, the most suitable function may vary from location to location.

6. There are many other ways of estimating the PDF for calculating the SPI and SPEI. Some approaches involve cluster analysis; which will produce spatially smooth statistical distributions. The results calculated here only apply to one method of calculating SPI and may not generalize to other SPI techniques.

7. The results are based on 8 years of drought index data. A larger sample would have been more robust.

8. The results may be sensitive to different ways of handling missing data.

9. The physical causes for temporal and geographical differences in interpolation accuracy were inferred rather than rigorously tested.

5. CONCLUSIONS

5.1. Discussion of Results

The objective of this thesis was to understand the spatial performance of interpolation of meteorological drought indices. Drought index values are influenced by a number of factors and the accuracy of spatial interpolation significantly varies as a function of these factors. In general, seasonality is the most significant factor affecting spatial accuracy followed by climatic region. Station density has relatively less influence, but it is important for resolving local patterns. The interpolation method (IDW or kriging) has the least influence on spatial accuracy (except for some specific cases). However, if additional interpolation methods had been tested, obviously some are not suited for interpolating drought indices and therefore would have had a large effect on accuracy. A one-size-fits-all approach may not give the best spatial accuracy when generating grids from station-based drought indices. The use of cross validation is recommended for examining the influence of different interpolation options. This helps to quantify and understand the performance before using particular datasets and interpolation methods. Modern software and computational systems makes this process faster and provides valuable information regarding spatial accuracy.

5.1.1 Objective 1: Which Interpolation Method Is Most Accurate?

Ordinary kriging with optimal functional fitting performed better than IDW methods. The IDW method with power parameter 2.5 also consistently gave better performance than IDW with power parameter 2.0. This is clearly seen in almost all the combinations evaluated. However the magnitude of improvement given by ordinary kriging varies from case to case. Differences in interpolation accuracy based on the interpolation method may be small when compared to the influence of seasonality and climatic region. The interpolation method makes a big difference for COOP PDSI, while it is marginal for USHCN PDSI. As the interpolation method is not the most significant influence driving accuracy, IDW 2.5 is a reasonable choice in most situations. However, for best accuracy the process of performing optimal kriging in R can be implemented easily using the Automap Library.

5.1.2 Objective 2: Which Drought Index Is Interpolated Most Accurately?

A number of paired drought indices were compared for different instances by their normalized errors. The 1-month SPEI gives slightly lower interpolation errors than corresponding values of 1-month SPI. This is attributed to the temperature input in its calculation. As PDSI measures long-term drought conditions, it was compared to 9-month SPI and 9-month SPEI. PDSI interpolation performs better than 9-month SPI and SPEI for COOP, but this does not hold true for USHCN. Multiscalar SPI is accurate when calculated using USHCN and it had the lowest interpolation errors amongst all the indices considered. Interpolation accuracy for multiscalar SPI with COOP dataset or multiscalar SPEI, when compared to their 1-month counterparts is lower. Drought indices that use temperature as an input are less spatially variable (more regionally consistent) than indices that are solely based on precipitation. The use of temperature reduces the influence of precipitation climatology on spatial inhomogeneity. It is important to realize this inherent variability when making conclusions about the moisture conditions of a location that does not have a local climatic data source.

5.1.3 Objective 3: How does Seasonality Influence Interpolation Accuracy?

Seasonality is the most significant factor that affects the accuracy of drought index interpolation. The highest errors were consistently observed for 1-month SPI and 1-month SPEI in months with high precipitation (generally summer) and with significant contributions from convective precipitation. The influence of seasonality is lower for PDSI because it measures long-term moisture conditions and therefore acts as a temporal smoother. Since only three months were compared for multiscalar SPI and SPEI, it is difficult to examine seasonal variations in interpolation error for these indices. Although it can be clearly concluded that there was very little seasonal variation in performance for the combinations of multiscalar SPI and SPEI that were considered in this thesis. Even with the use of the best interpolation method (optimal kriging) and highest station density, relatively large interpolation errors were found during the summer months (e.g. Southeast climatic region). Seasonal variation was lower in the western U.S. (because it has a different precipitation regime that features a winter precipitation maximum), but it still was the most significant factor that influenced interpolation accuracy. It is concluded that seasonal variation in precipitation is the most important factor affecting spatial interpolation accuracy. This means that the depiction of moisture conditions during the summer is less accurate than the depiction of moisture conditions during the winter.

5.1.4 Objective 4: How does Interpolation Accuracy Vary Over the United States?

Mean absolute errors from the cross validation were interpolated to a regular grid to show the spatial variations in interpolation error across the U.S. Although the overall mean absolute errors for kriging interpolation of PDSI using both COOP and USHCN datasets were similar, the spatial pattern of errors were different. Due to higher density of COOP stations, the errors vary considerably from location to location and this is not seen for USHCN. USHCN has a much smoother and more homogeneous error field because the station spacing and station density are more homogeneous than COOP. Although similar differences between COOP and USHCN are also observed for 1-month SPI and 1-month SPEI the differences are not as marked as the PDSI. Errors across the country are consistently higher in July than January. The highest errors are observed in the Western and West North Central climatic regions because these areas have significant topographical variation. Higher errors in summer can also be seen in Florida and Southeast. The lowest errors are seen through much of the Great Plains, midwest, and northeast, as well as some parts of the western U.S. Mapping the interpolation errors allows for a visual assessment of errors and some of the patterns that were observed were not apparent in the analysis of climatic regions.

5.1.5 Objective 5: How does Station Density Affect Interpolation Accuracy?

For almost all cases involving 1-month SPI and 1-month SPEI, COOP had less error than USHCN. One exception is that multiscalar SPI had significantly better spatial accuracy for USHCN than for COOP. This is attributed to the lack of sufficient length of record for COOP data especially for longer SPI time scales (i.e., 9-month and 12-

month). In a few regions such as Western or EastNorthCentral region where the difference of station density between USHCN and COOP is significant, the improvement can be clearly seen. The influence of station density on spatial accuracy is definitely higher than interpolation methods, but lower than climatic region or seasonality. Except for cases like multiscalar SPI, the use of COOP stations will help characterize local patterns in moisture conditions that are not seen with USHCN because COOP has a higher station density. It is important to assess other sources of errors that can possibly come from using stations with a shorter record.

5.2 Implications

Drought indices are commonly converted to spatial grids for drought monitoring and it is important to examine the different factors that affect the spatial accuracy of these representations. Cross validation can be used to examine how a variety of factors influence the accuracy of depictions of moisture conditions. Cross validation is relatively easy to implement and provides an objective measure of accuracy. It is useful for determining the best approach for generating depictions of drought conditions. A custom solution to determining interpolation technique which is a function of drought index, region, season and dataset (based on quality) should be used. In some conditions (e.g. summer in the southeastern U.S.) a higher density of stations will not necessarily improve the interpolation accuracy for drought indices. However, having a higher spatial density of stations is helpful for detecting local patterns, especially for self-calibrated PDSI.

It is important to understand the relative component of different errors (function fitting, observational and spatial interpolation) before making conclusions regarding drought conditions. It is possible that even drought indices that have high interpolation accuracy may mischaracterize drought conditions due to other error sources (e.g., consistently underestimating or overestimating values in a region).

5.3 Future Research

An approach to drought monitoring in which interpolation is performed from historical data of precipitation/temperature and drought information is calculated for all the points in the grid based on historical interpolated grid values can help make better use of additional variables (elevation, topography) for constituent variables (precipitation, temperature) to improve spatial accuracy.

One way to improve the accuracy of depictions of drought conditions is to determine the correct trade-off between length of record and density of stations for drought index under consideration. Therefore, future research should investigate methods for incorporating meteorological data from multiple sources (e.g. using data from volunteer weather stations with good quality and using interpolated historical data to enable calculation of drought index at that location). Such data can be incorporated into a modified kriging method to help in identifying the local variations that are observed when comparing the performance of one example across U.S.

A simple easy to use GUI based software package that takes in input data, calculates drought indices, generates cross validation errors and assesses influence of different factors statistically as done in this thesis can help many researchers to simplify the process of optimizing spatial accuracy. This can be implemented using most of the existing libraries presently available in R (spatial interpolation, cross validation), SPEI for drought indices and writing a wrapper for PDSI. The potential to serve this software system in a browser (using R-server) can help multiple people with drought index data to use it to optimize it for their own use as well as share best fits with others.

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