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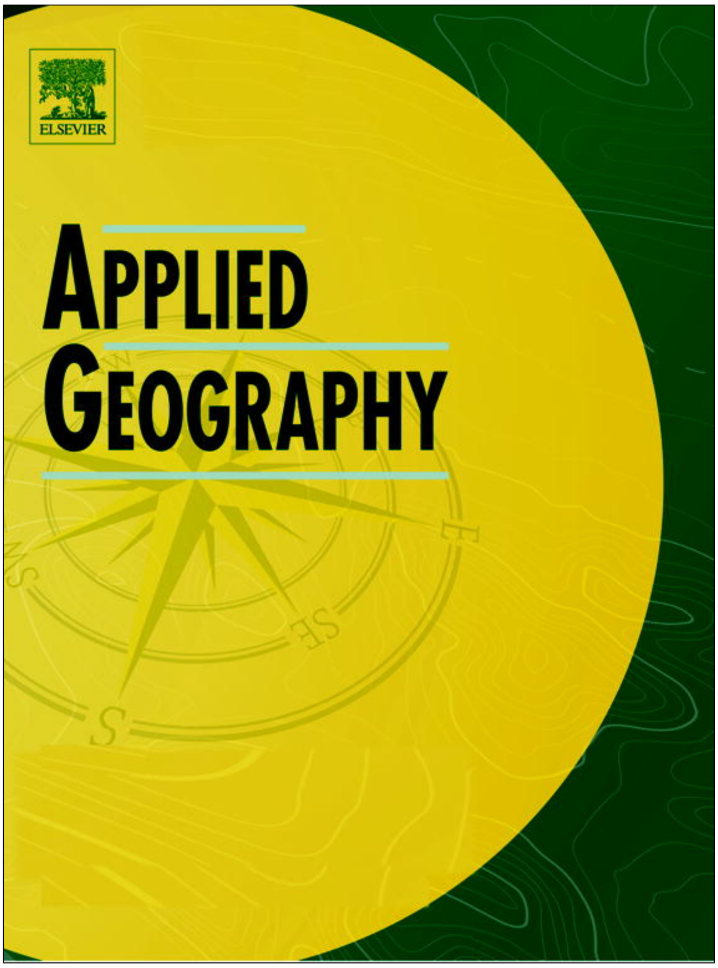
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Spatial interpolation of temperature in the United States using residual kriging

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A B S T R A C T

Temperature is one of the most important factors influencing every aspect of life. In response to the increasing greenhouse effect in recent years, the demand for understanding the spatial variability of temperature in the U.S. has risen dramatically. To meet this need, we developed a statistical model for constructing a gridded temperature dataset over the mainland United States. Based on the data collected from 922 meteorological stations in the U.S., temperatures at over 5000 unknown locations were predicted in January and July, 2010. This study utilized variables of latitude and longitude (model 1), and latitude, longitude and elevation (model 2) as inputs in a residual kriging method to interpolate the average monthly temperature. We also estimated temperatures at the same locations with the kriging function of ArcGIS and compared the performances of our models with that of ArcGIS. We found that, by adding an elevation factor, our model (model 2) had a better predicting performance than that of ArcGIS kriging function in both January and July. However, only estimation in July was not different from the observation. This suggests that our kriging model is capable of capturing the spatial variability of temperature, but it is sensitive to season. The successful interpolation of July temperature indicates that the accuracy of interpolation can be improved by adding appropriate variables. Seasonal models developed in future research can be valuable tools for meteorological and climatological research.

Introduction

Temperature is one of the most important atmospheric variables which directly impact physical and biological processes (Li et al., 2013; Stahl et al., 2006). Temperature can be a basis for understanding many processes such as evapotranspiration and plant distribution (Dodson & Marks, 1997; Trisurat, Shrestha, & Kjelgren, 2011). With increasing concentration of greenhouse gases, climate change causes growing concerns (Boykoff & Boykoff, 2007). Since 1895, the average annual temperature of the contiguous United States increased by 0.07 °C per decade. In 2010, it was 12.1 °C, 0.6 °C above normal (NOAA National Climate Data Center, 2010). 2010 was among the two warmest years by 2011. Twelve eastern US states had their warmest summer in 2010 (Blunden, Arndt, & Baringer, 2011).

Knowledge of the spatial variability of temperature is required to meet the need of assessing the recent climate change and greenhouse effect in the U.S. However, this is limited by the current spatial coverage of climate datasets. Temperature data is always collected from irregularly arrayed and discretely distributed meteorological stations. Especially in mountainous regions, there are insufficient meteorological stations (Rolland, 2003). Therefore, there is a rising demand for creating quality gridded climatological datasets through interpolation methods. Previously, spatial interpolations of temperature in the U.S. were mostly at regional bases (Brown & Comrie, 2002; Hunter & Meentemeyer, 2005; Serbin & Kucharik, 2009). To our knowledge, only few studies developed interpolation models for the entire country. Willmott and Matsuura (1995) proposed annual interpolation techniques incorporating spatially high-resolution digital elevation information, an average environmental lapse rate, and high-resolution long-term average temperature for 1920–1987. Another study used a combination of daily observations and Parameter-Elevation Regression on Independent Slope Model (PRISM) maps as inputs to interpolate daily temperatures over the conterminous United States for 1960–2001 (Di Luzio et al., 2008). In another study, PRISM interpolation method was also used to develop datasets of monthly minimum and maximum temperature from 1971 to 2000 for the conterminous United States (Daly et al., 2008). Qi et al. (2012)

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created county-level monthly average temperature using elevation as a covariate in the US in 2007. Spatial interpolation of mean temperature in short-term (monthly) always presents more challenges than annual or long-term mean temperature, and the implement of temperature interpolation in the recent year with limited interpolators presents even greater complexity.

A number of methods have been developed for interpolating climate data. Over the past several decades, kriging has become an essential tool in the field of geostatistics. Previous researches have demonstrated that kriging is a better interpolation method with high accuracy and low bias compared to other methods (Li, Cheng, & Lu, 2005; Mahdian, Bandarabady, Sokouti, & Banis, 2009; Yang, Wang, & August, 2004). The advantage of kriging over other non-geostatistical methods is that the spatial variation structure is estimated through variogram and takes spatial autocorrelation into consideration (Aalto, Pirinen, Heikkinen, & Venäläinen, 2013). The principle of kriging is straightforward. It is a linear combination of weights which are determined by the spatial variation structure (Hattis, Ogneva-Himmelberger, & Ratick, 2012). There are different forms of kriging: ordinary kriging, simple kriging, universal kriging, cokriging as well as residual kriging (Sluiter, 2009).

The real spatial processes always show surface trend or drift which is the variation of the attribute depending on other variables. Latitude and longitude are always the underlying effects relative to temperature (Zhao, Nan, & Cheng, 2005). Elevation was also found to be highly associated with temperature (Samanta, Pal, Lohar, & Pal, 2012; Stahl et al., 2006). In addition, other factors including water bodies and local terrain also contribute to the temperature variation (Daly et al., 2008; Minder, Mote, & Lundquist, 2010). The distance to large water body greatly influences the temperature pattern. The difference of summer maximum temperature in 5 km and 20 km distance to the water is above 20 °C (Daly et al., 2002). Terrain-related factors such as slope orientation and slope gradient affect the amount of sun radiation on the surface of the land and then temperature (Zhao et al., 2005). Residual kriging can address the spatial data with broad regional trend. It is a two-step algorithm. The first step is to identify and remove the systematic trend in the spatial process. The second step is that the remaining part, the stationary residuals, are kriged to obtain estimations. The final product is the sum of the trend and the kriging residuals (Holdaway, 1996). Residual kriging is extensively used in meteorological data analysis (Sluiter, 2009). This method of decomposing the observation into a surface trend plus a residual value is better than interpolating directly on the observed data, especially when it applies to a large spatial area (Holdaway, 1996; Liao & Li, 2004). Dryas and Ustrnul (2007) compared different interpolation methods and found the residual kriging method as the best method of all to interpolate the monthly and seasonal average temperatures in Poland. This method also performed as the best method to predict temperatures in Spain and Slovenia (Sluiter, 2009). So far, few have been known to use residual kriging in interpolating temperatures for the entire U.S. Given the diversity of spatial variability of monthly temperature in such a large region, we sought to develop a simplified interpolation model by using detrending to account for the latitude–longitude and the elevation effects.

Geographic Information System (GIS) plays an important role in geospatial analysis (Silberman & Rees, 2010) and produces reliable climatological datasets. Meanwhile, with the development and proliferation of computer technology, statistical software also becomes a popular tool in geostatistical analysis such as SAS software (Statistical Analysis System). However, comparison of the accuracy of kriging interpolations in ArcGIS and in statistical software has been rarely studied. This study also aims at identifying the performance of kriging model fitting in SAS as compared with ArcGIS.

Based on the above literature review, this study aims to develop a statistical model to interpolate the average monthly temperatures in the U.S. in January and July 2010, to test the accuracy and precision of the proposed model by comparing it with ArcGIS kriging function, and to identify the variability of average temperatures in January and July in 2010. The section that follows introduces data and data sources as well as model construction and validation. A discussion of results is presented in the next section regarding the model performance and spatial variation of air temperature in the U.S. Finally, conclusions based on the paper's major findings are summarized in the last section.

Methodology

Study area and data collection

The study area for this analysis mainly includes the mainland of the United States located at 24–50°N and 68 to 125°W (Fig. 1). The study region is characterized by a variety of climate patterns. It ranges from humid continental in the north to humid subtropical in the south. It also includes many other types such as the tropical climate in southern Florida, the semi-arid climate in the west of the Great Plains, the arid climate in the Great Basin as well as the alpine, desert, and oceanic climates.

The dataset was obtained from the global historical climatology network (GHCN-Monthly) database, version 3, in oceanic and atmospheric administration national climate data center for the year 2010. The version 3 dataset is subjected to quality control and homogeneity adjustment (NCDC, 2010a). The data file includes the daily-updated monthly average, maximum, and minimum temperatures. Likewise, it also includes basic geographical station information such as latitude, longitude, elevation, type of topography, surrounding vegetation and population class, etc. Analysis was restricted to stations with no missing observations. A total of 922 historical climate network stations were included in this study. The latitude, longitude and elevation were used as predictors to interpolate the monthly average temperature. Elevation of the selected stations ranges from −59.1 m to 2763 m. The categories of vegetation vary across warm grassland, warm crop and warm field woods in the south to cool grassland, cool crop and cool conifer in the north. 60% of the stations are in rural areas with a population of less than 10,000 persons, 24% are in suburban areas (10,000–50,000 persons), and 16% are in urban areas (>50,000 persons). January and July were selected as representatives of winter and summer months, respectively.

Interpolation

The trend estimation

The first multiple regression model (model 1) for estimating the underlying trend was developed on the geographic coordinates latitude and longitude. It was formulated as $T = a + bx + cy + dx^2 + ey^2 + fxy$. The dependent variable T is the monthly average temperature in °C, the independent variables are x (latitude in degree), y (longitude in degree), the second-order polynomials (x^2, y^2) and the interaction term (xy).

The second multiple regression model (model 2) was developed on latitude, longitude and elevation, and was formulated as $T = a + bx + cy + dx^2 + ey^2 + fxy + gz + hzx + izy$. Predictors of this model are the same as model 1 except for the addition of elevation (z), the interaction between elevation and latitude (zx) and the interaction between elevation and longitude (zy).

We ran the two models for the January and July datasets, respectively. A step-wise method was used to select the significant predictors. The first predictor entered into the model is considered to have the highest prediction power of monthly average temperature. The step would be stopped when there were not any more variables entered or removed from the model. There is a model *R*-square in each step indicating the prediction power of the model.

Residual variogram

The difference between the observation and the regression estimation is the residual. *Moran's I* (Moran, 1950) and *Geary's* c (Geary, 1954) were used to measure the spatial autocorrelation among the residuals. The semivariogram is an estimator of variation attributed among spatial locations (Valeriano & Rossetti, 2012). The experimental semivariogram is calculated as half of the average squared difference of all the data pairs with the distance h in the spatial range:

$$\widehat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2$$

where $\widehat{\gamma}(h)$ is the experimental semivariogram, h is the lag distance between two locations, $N(h)$ is the number of pairs of data locations with h distance apart, and $Z(x)$ is the measured temperatures at two locations (Wang, Zhang, & Li, 2013). The semivariance increases as lag distance increases and is asymptotically close to the maximum variance, the sill. The distance corresponding to the sill is called range. Due to the random error or measurement error (nugget effect), the semivariogram does not go through the origin (Valeriano & Rossetti, 2012). Evaluating and modeling the spatial variation structure is very critical for prediction using kriging. Different kinds of mathematic models have been used to model the experimental semivariograms including the spherical model, the gaussian model and the exponential model (Valeriano & Rossetti, 2012). Based on criteria statistics indicative of goodness of fit (e.g. The Akaike Information Criterion (AIC) (Akaike, 1974)) and the accuracy of the prediction, the best fitted model was selected.

For a stochastic spatial process, the spatial correlation structure may depend on directions. Directional semivariograms were plotted in 12 directions with the increment of 15° (0°, 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, and 165°). In the case of anisotropy, the theoretical model is fitted in the directions of major and minor spatial continuity, respectively. Automatic fitting using the weighted least-squared nonlinear regression estimates the parameters such as nugget, sill and range in each direction, respectively.

Temperature prediction

Based on the spatial correlation structure obtained in 2.2.2, the residuals were predicted at regularly spaced 115 × 53 geographic grids with an interval of a half degree in both the *x* (longitude) and *y* (latitude) coordinator axis. Elevations at these unmeasured locations were estimated by the ArcGIS software. The estimation of elevation was generated at 5298 unknown locations due to its inaccessibility in the boundary areas. The final products were denoted as predictions of model 1 (without elevation) (6095 locations) and model 2 (with elevation) (5298 locations), respectively. Our model development was implemented by SAS 9.2.

Model validation

In order to identify the precision of our interpolation, we conducted a validation test. The validation dataset was downloaded from NCDC (NCDC, 2010b) and comprised of temperature records in 344 divisions nationwide. NCDC divides each state into divisions ranging from two to ten, except for Alaska and Hawaii. Temperatures interpolated by the kriging algorithm in the ArcToolbox of ArcGIS were used as a benchmark for our prediction. Through ArcGIS, we computed the average temperature of each division based on temperatures predicted by our models and temperatures estimated from the ArcGIS kriging function. We compared these two datasets of predictions with the measured temperatures of divisions by a paired *t*-test.

The difference between our prediction and the original observation as well as the ArcGIS extracted prediction and the original observation were calculated in each division. All predictions were classified into five categories according to the differences (−9.90 to −5.00, −4.99 to −2.50, −2.49 to 0.00, 0.01 to 2.50, and 2.51 to 4.56

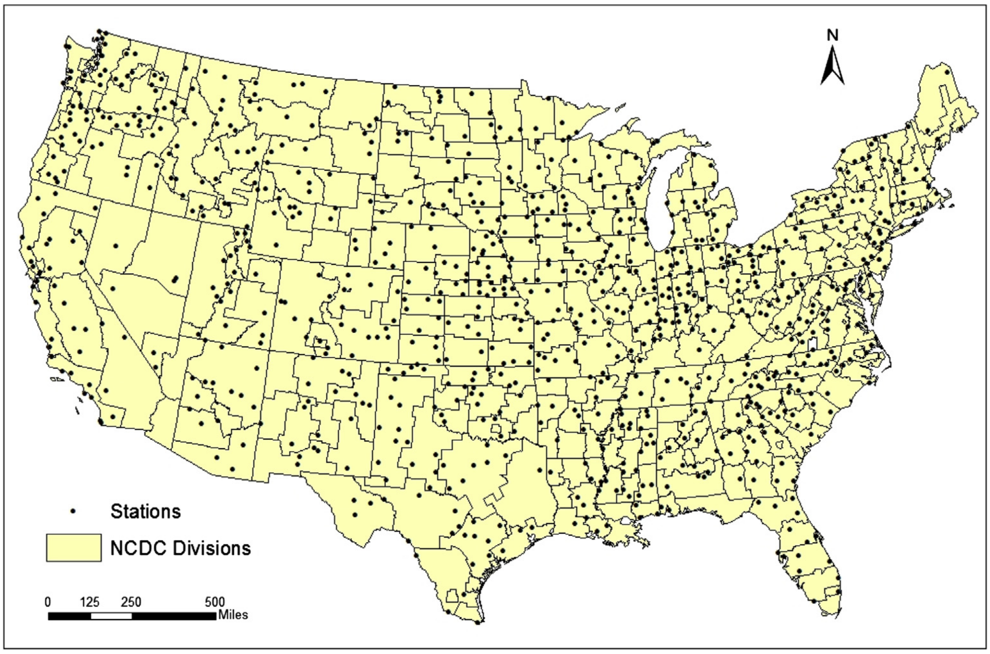

Fig. 1. Distribution of meteorological stations in the study area.

Table 1
Estimated coefficients of multiple regression models for mean temperatures in January and July.

Coefficients	Model 1		Model 2	
	January	July	January	July
Intercept	269.1761*	15.3238*	236.9786*	−30.0041*
Latitude	−4.5375*	0.2985	−3.7901*	1.1517*
Longitude	3.4872*	−0.3399*	3.1534*	−0.9318*
Latitude²	0.0265*	−0.0159*	0.0202*	−0.0218*
Longitude²	0.0158*	−0.0031*	0.0150*	−0.0054*
Latitude × longitude	−0.0140*	−0.0049*	−0.0110*	−0.0016
Elevation			0.0027	−0.0155*
Latitude × elevation			0.0001*	−0.0001*
Longitude × elevation			0.0001*	−0.0001*

* Significant at 5% significance level.

(°C)). The distribution of the difference was compared among our models and the ArcGIS interpolation. The maps of these differences were produced by the GIS 10.1. The performance of our models and ArcGIS predictions on the division level was further compared by the three criteria: mean absolute error (MAE), mean biased error (MBE) and root mean squared error (RMSE) (Duncan & Biggs, 2012; Wang et al., 2013). MBE measures the bias of the prediction. Positive or negative MBEs indicate over, or under-estimation of the observed data (Volin et al., 2008). MAE measures how far the prediction from the observation in error and RMSE provides the magnitude of the residual error (Zhao et al., 2005). For the evaluation of model performance, RMSE is more powerful (Willmott, 1981).

Results and discussion

Trend estimation

The results of step-wise selection and multiple regression model fitting are summarized in Tables 1 and 2. All variables kept in the models are significant at the level of 0.15 (0.15 is the defaulted significant level of the stepwise selection in SAS) except for elevation factor in January. Elevation is kept in the January model because the interaction terms between elevation and geographic variables (latitude and longitude) are significant. In model one, the geographic variables can explain 88.02% (model R^2) of the total variation of temperature in January and 65.46% in July. Thus, geographic variables have pronounced effects on the variability of monthly average temperature. Among them, latitude and latitude^2 are the most effective predictors in January and July, respectively. 45.07% of the total variation in January is attributed to latitude and 55.13% in July is associated with latitude^2. Longitude also has a significant impact on temperature predictions. Longitude^2 contributed 16.64% and 7.51% of total temperature variation in January and July, respectively.

Table 3
Descriptive statistics of the observed and predicted temperatures in January and July.

Statistics	Observed		Model 1		Model 2	
	January	July	January	July	January	July
Max (°C)	21.10	40.87	32.32	31.57	26.29	29.94
Min (°C)	−15.30	12.26	−14.85	10.86	−14.71	14.56
Mean (°C)	−1.02	24.09	3.68	24.09	1.71	24.08
S.D. (°C)[a]	6.58	3.64	10.44	4.13	9.32	3.69

[a] S.D.: Standard deviation.

In model two, 45.02% of total temperature variation was ascribed to latitude and 16.53% was ascribed to longitude^2 in January. Latitude^2 contributed 56.60% of total variation whereas longitude^2 contributed 0.61% in July. The model R^2 increases to 90.85% in January and 75.39% in July. This indicates that the addition of elevation and the associated interaction terms can improve the spatial representation of the monthly temperature. 4.60% of the spatial variation in January temperature is accounted for elevation and for July it is 2.67%. Given the diversity of the terrain over the broad scales and the complexity of multivariate models in the present study, it is reasonable to have relatively low partial-R^2s (the percentage of variation explained by the variable) of elevation. This result indicates that there is a higher correlation between temperature and elevation in January than in July. It is in accordance with the results in previous studies (Hudson & Wackernagel, 1994; Kurtzman & Kadmon, 1999). Overall, latitude has more impressive effect on temperature than longitude in both models although longitude is also significant to temperature variation, especially in January. This result is consistent with the research on Minnesota (Holdaway, 1996). This could be partially because, in winter, the polar jet stream brings the large low pressure system from the Northern Pacific Ocean. A negative Arctic Oscillation also brought cold arctic air to the south in the U.S. in 2010 (Blunden et al., 2011). In summer, the warm effect from the southwest and southeast United States prevails.

Residual semivariograms

The semivariogram was estimated with the trend removed. Both coefficients of Moran's I and Geary's c are significant for residuals, indicating that there are strong spatial correlations among the residuals in both January and July ($p < 0.0001$) (not shown here). In fact, a general model fitting was applied to estimate the residual semivariogram despite the fact that no model can perfectly describe the realistic semivariogram (Holdaway, 1996). In this study, according to the AIC values (a smaller AIC value is better) and the fitted theoretical semivariograms, the exponential model (equation shown below, where c_0 is the nugget variance, c is the sill,

Table 2
Summary of step-wise selection in multiple regression models.

Step	Model 1				Model 2			
	January		July		January		July	
	Variable entered	R^2	Variable entered	R^2	Variable entered	R^2	Variable entered	R^2
1	Latitude	0.4507	Latitude²	0.5513	Latitude	0.4502	Latitude²	0.5660
2	Longitude²	0.6171	Longitude²	0.6264	Longitude²	0.6155	Elevation × longitude	0.6556
3	Longitude	0.8353	Latitude × longitude	0.6472	Longitude	0.8343	Latitude	0.6739
4	Latitude × longitude	0.8666	Longitude	0.6536	Elevation	0.8803	Longitude²	0.6800
5	Latitude²	0.8802	Latitude	0.6546	Latitude × longitude	0.8987	Longitude	0.7243
6					Latitude²	0.9065	Elevation	0.7510
7					Elevation × longitude	0.9077	Elevation × latitude	0.7533
8					Elevation × latitude	0.9085	Latitude × longitude	0.7539

Table 4
Paired *t*-test between observed values and predicted values from ArcGIS, model 1, and model 2.

	January			July		
	ArcGIS[a]	Model 1[b]	Model 2[b]	ArcGIS	Model 1	Model 2
p-Value	<0.01*	<0.01*	<0.01*	0.28	0.30	0.26

* Significant at 5% significance level.
[a] Paired t-test is conducted between ArcGIS interpolations and observed temperatures.
[b] Paired t-test is conducted between interpolations from our models (model 1 and model 2) and observed temperatures.

Table 6
Comparison of validation error statistics of model 1, model 2, and ArcGIS interpolation

		MAE (°C)	MBE (°C)	RMSE (°C)
January	Model 1	1.59	−0.64	2.62
January	Model 2	0.92	0.36	1.35
January	ArcGIS	1.58	−0.64	2.57
July	Model 1	2.39	−1.47	3.47
July	Model 2	0.73	0.09	1.20
July	ArcGIS	2.07	−1.35	3.06

Mean absolute errors (MAE), mean biased errors (MBE), and root mean squared errors (RMSE).

r is the range, h is the distance and $\gamma(h)$ is the semivariance) was chosen as it best fits the experimental semivariogram in both January and July.

$$\gamma(h) = c_0 + c\left(1 - \exp\left(\frac{-h}{r}\right)\right) \quad h > 0$$

$$\gamma(h) = 0 \quad h = 0$$

Evidences of anisotropic semivariograms are observed at 12 directions (0°, 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, and 165°). The parameter estimations were obtained in the directions of major and minor spatial continuity.

Temperature prediction

Statistics of observed and predicted temperatures are summarized in Table 3.

Statistics of predicted temperatures by two models have differences. The range of the predicted values is smaller in model 2 than that of model 1, especially in July. The standard deviation obtained by model 2 is slightly smaller than that by model 1, but both of them are inflated compared with that of the observation. The reason could be partially due to the expansion of predicted locations (6095 predicted locations in model 1, 5298 locations in model 2, and 922 observed stations). In general, the predicted variation of temperatures in January is larger than that in July. Previous researchers draw similar conclusions in northern Spain (Benavides, Montes, Rubio, & Osoro, 2007) and northern Italy (Rolland, 2003). It is partially owed to the fact that temperature is more related to elevation in winter than in summer (Hudson & Wackernagel, 1994; Kurtzman & Kadmon, 1999).

Means produced by our models are comparable to that of the observation in July. Both model 1 and model 2 generate unbiased means. In contrast, both of the model-derived means are overestimated in January. However, the mean predicted by model 2 has a smaller bias than model 1. As a whole, our predictions are higher than the NCDC records in the second half of 20th century (1950–2000) (−1.07 °C in January and 23.16 °C in July) indicating that global warming is a prevailing climate issue (NCDC, 2010a).

The predicted temperatures of the Pacific Ocean coast in the southwest and the Gulf of Mexico in the south show warmer gradients than that in the adjacent lands in January. Conversely, in July, the western coasts and southern water areas have noticeably cooler temperatures than the surrounding lands. This result is identical to the previous study (Courault & Monestiez, 1999) which is due to the "muffle effect" of the sea.

Model validation

According to the paired *t*-test, we summarized the model validation results in Table 4. In January, both temperatures predicted from our kriging models and those extracted from the ArcGIS kriging function are significantly different from the measured temperatures at the divisional base ($p < 0.01$). In July, however, both model 1 and model 2 have better performances than that of January. The interpolations obtained from model 1, model 2, and ArcGIS are demonstrated the same as the observed temperatures at a 5% significance level ($p = 0.30$, 0.26, and 0.28, respectively) (Table 4). The result that the prediction power differs among months indicates that the model performance is sensitive to season.

In January, the ArcGIS prediction has the largest percentage (20.23%) of the absolute bias above 2.50 °C, followed by the prediction of model 1 (19.35%) and model 2 (7.04%). To the contrary, the prediction of model 2 has the largest percentage (92.96%) with a minor bias in the span of ±2.50 °C. Similarly in July, a larger percentage of prediction by model 2 (93.26%) distributes in the span of difference within ±2.50 °C than that of ArcGIS (70.38%) and model 1 (65.40%). Meanwhile, 34.60% of the prediction by model 1, 29.62% of the ArcGIS prediction and 4.99% of the prediction by model 2 fall into the range of the absolute bias above 2.50 °C. In addition, the prediction of model 2 gives the lowest MAE, MBE and RMSE compared to those of model 1 and of ArcGIS in both January and July, respectively (Tables 5 and 6). MAE, MBE, and RMSE of model 2 are 0.92 °C, 0.36 °C, and 1.35 °C in January; and 0.73 °C, 0.09 °C, and 1.20 °C in July, respectively. These results indicate model performance is improved by adding the elevation as an interpolator and this applied improvement makes our model even more accurate than the ArcGIS.

Table 5
Frequency (number and percentage) of differences between observed values and predicted values from Model 1 Model 2 and ArcGIS interpolations.

Difference (°C)	January			July		
	Model 1	Model 2	ArcGIS	Model 1	Model 2	ArcGIS
$\geq -9.90 \leq -5.00$	31/9.09%	2/0.59%	32/9.38%	50/14.66%	2/0.59%	43/12.61%
$\geq -4.99 \leq -2.50$	26/7.62%	6/1.76%	30/8.80%	54/15.84%	4/1.17%	53/15.54%
$\geq -2.49 \leq 0.00$	43/12.61%	104/30.50%	34/9.97%	55/16.13%	152/44.58%	62/18.18%
$\geq 0.01 \leq 2.50$	232/68.04%	213/62.46%	238/69.80%	168/49.27%	166/48.68%	178/52.20%
$\geq 2.51 \leq 4.56$	9/2.64%	16/4.69%	7/2.05%	14/4.10%	11/3.23%	5/1.47%
No data					6/1.75%	
Total	341/100%	341/100%	341/100%	341/100%	341/100%	341/100%

As stated above, model 2 has a better performance in prediction than ArcGIS. Maps of differences between predictions (of model 2 and of ArcGIS) and the observation were shown in Figs. 2 and 3. In January, the difference between the ArcGIS interpolation and the observation varies from −9.30 to 4.56 °C whereas that between our interpolation and the observation is in the range of −5.60 to 5.51 °C. The ArcGIS interpolation shows marked underestimation with the amplitude of −9.30 to −5.00 °C in the north of the Pacific Alaska region, the Pacific region, the Rocky Mountain region, a small part of the Great Lakes region, and the Central Plains region (Fig. 2a). Our prediction shows moderate underestimation varied from −4.99 to 0.00 °C in these areas (Fig. 2b). Overall, our interpolation shows less difference from the observation than the ArcGIS interpolation despite that both interpolations are significantly diverse from the observation in January.

In July, the difference between ArcGIS interpolation and observation varies from −9.90 to 5.79 °C whereas that for our model is −7.20 to 4.46 °C. The dominant influence of negative bias encompasses a broad area almost covering all of the studying area. The downward trend of the interpolation appeared in the map demonstrates that the interpolation derived from the ArcGIS has a large variation away from our base data in July (Fig. 3a). However, the departure of our interpolation away from the observation is smaller than that of the ArcGIS interpolation. Our interpolation captures most of the temperature gradients and most areas of the map show moderate to minor bias within ±5.00 °C span (Fig. 3b).

Overall, some locations in western US are characterized with large discrepancies from observations upwardly or downwardly in both January and July. Another study also found that the interpolation of minimum and maximum temperatures shows larger error

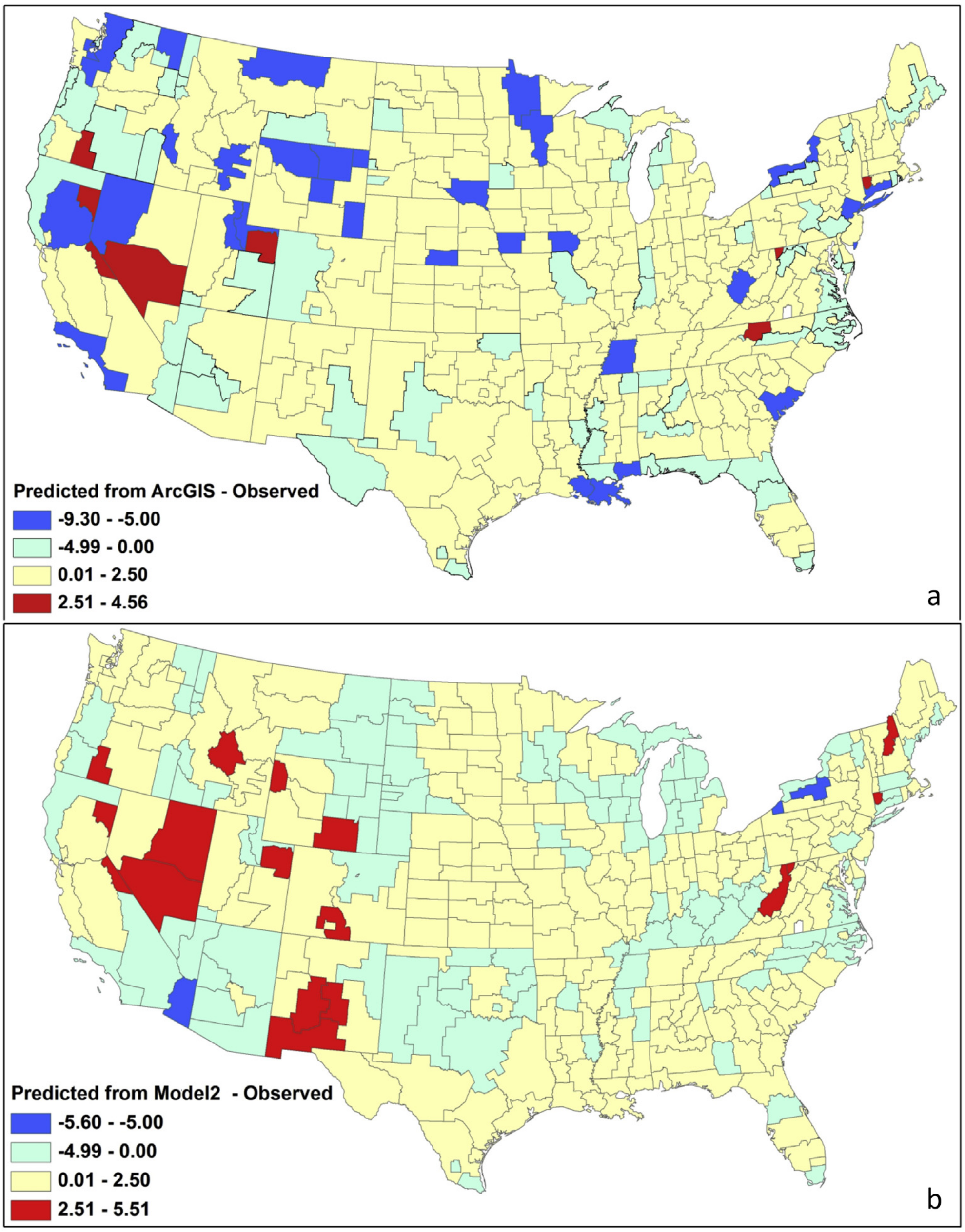

Fig. 2. Temperature of U.S., January 2010. (a) Differences between temperatures interpolated from the ArcGIS Kriging function and observed temperatures (°C); (b) Differences between temperatures interpolated from our model (Model 2) and observed temperatures (°C).

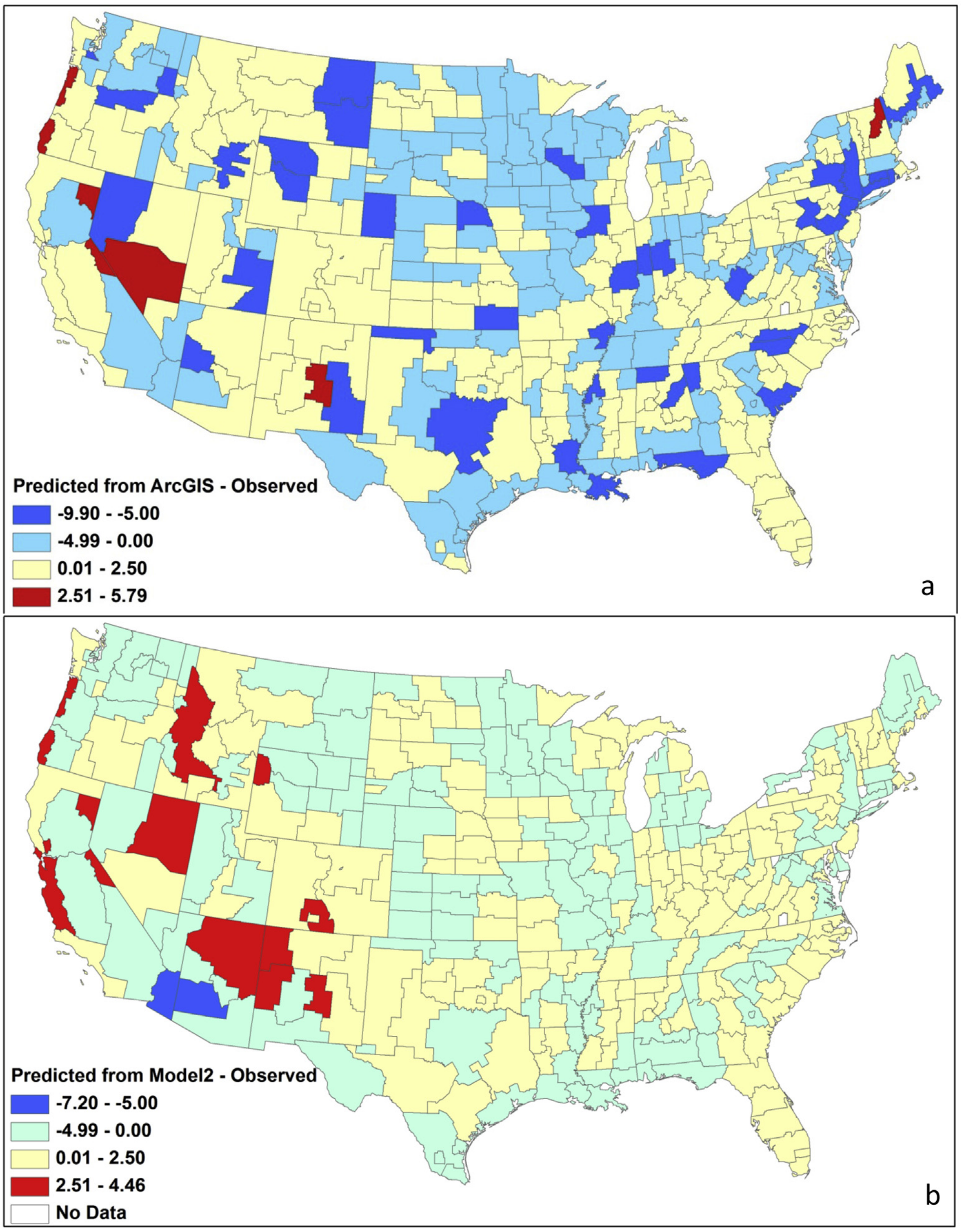

Fig. 3. Temperature of U.S., July 2010. (a) Differences between temperatures interpolated from the ArcGIS Kriging function and observed temperatures (°C); (b) Differences between temperatures interpolated from our model (Model 2) and observed temperatures (°C).

in western U.S. than central and eastern U.S. (Daly et al., 2008). The reason could be ascribed to the complex terrain in the western mountainous areas as well as the coastal effect. It suggests that terrain effects in the mountainous area does not only include the direct effect of elevation on temperature, the slope orientation and slope angle also influence the temperature (Zhao et al., 2005). In the middle latitudes of the Northern Hemisphere, the temperature in the north-facing slopes has a huge difference from that in the south-facing slopes at the same elevation. It also indicates that the effect of coast proximity is pronounced in the area adjacent to coastline. Meanwhile, the spatial distribution of the stations is not homogenous over the study area. Another reason for the large bias in western U.S. in this study could be that the meteorological stations distribute more sparsely in the west than in other areas (Fig. 1). Therefore the resolution of the base dataset is also a very important factor influencing the accuracy of interpolation. In addition, the precision of interpolation is affected by the edge effect (van der Veer, Voerkelius, Lorentz, Heiss, & Hoogewerff, 2009). The boundary areas have larger deviations away from the observations than the center areas regardless of the season.

In order to obtain unbiased prediction, increase in the resolution of observation can reduce the error of prediction. Based on a high-resolution dataset (5685 stations nationwide) with topological and climatological information, Willmott and Matsuura (1995) dramatically increased the accuracy of interpolation for a long-term annual average temperature in the US. Qi et al. (2012) used data from 5435 weather stations to constitute the county-level (3109 counties) monthly average temperature. In spite of the relatively low spatial resolution of the base dataset (922 observation stations nationwide) in this study, the temperature data generated by our study is relatively in high resolution (over 5000 locations). It is also unbiased and even shows an outperformance over the ArcGIS interpolation in July. With a high-resolution dataset, our model may generate even more accurate predicted temperatures.

Elevation, latitude, longitude, distance to coastline and distances to four types of mainland use were found to be efficient in estimating the monthly average air temperature in Peninsular Malaysia (Yunus, Jaafar, Mahmud, Shafie, & Idris, 2012). Another study used a knowledge based system to create the gridded climate datasets over the U.S. They took distance, elevation, cluster, vertical layer, topographic facet, coastal proximity, and effective terrain factors into consideration (Di Luzio et al., 2008). Encompassing elevation in our model is proved to be helpful to improve the model performance in the present study. Other appropriate interpolators can be added into our model to further improve the accuracy, such as coastal proximity and terrain-related factors. A more sophisticated model for the estimation of terrain-related factors is also required.

The interpolation method (residual kriging) used in this study is easy to implement and suitable for interpolation over a large area. The difference of model performance in January and July is consistent with the study in California (Hunter & Meentemeyer, 2005). It indicates that the selection of the interpolation method and the theoretical model is the key aspect for spatial prediction.

Conclusions

This paper contributes to the literature by developing a new kriging model for interpolating the air temperature in the mainland of the U.S. in 2010. This spatially continuous dataset created for the year 2010 has the potential to fulfill the requirement of identifying the amount of spatial variation inherent in temperature. The decomposition of temperature into a large-scale trend and a small-scale variation is a simplified method for interpolation over a large area. In fact, it is increasingly desirable to propose a simple method for the estimation of temperature over large distances. The results show that the large-scale surface trend describes the relationship between the monthly temperature and the geographic (latitude and longitude) as well as topographic (elevation) variables. It also can be concluded that temperature is more dependent on latitude than longitude. The small-scale variation takes the dependence of spatial variability with direction into consideration which makes the interpolation more accurate and satisfactory. The $0.5°$ latitude $\times$ $0.5°$ longitude predictions of temperature generated in this study are a GIS-compatible dataset and have a uniform spatial coverage.

Furthermore, a modified model including elevation as an interpolator is able to obtain a more accurate prediction in winter and summer months. We compared our method with the ArcGIS kriging function to validate our models. The results are encouraging given the simplicity of the proposed method. The residual kriging method contributes to an unbiased interpolation of average temperature in July in 2010. More importantly, its result outperforms interpolation by the ArcGIS kriging function. This method does not generate unbiased interpolation in January since temperature is a complex climate component and many factors affect its fluctuation. Besides, the relative low resolution of the base dataset and the limited extended information of the unknown locations present a challenging test for interpolation over such a large geographic domain. The fact that our prediction successfully generated the surface trend of temperature and captured the reasonable magnitude of temperature suggests that residual kriging is a broadly based method capable of interpolating and interpreting the climatological and meteorological variation.

In future studies, we are planning a further improvement of the proposed method to address associated needs. The spatial variability of temperatures is sensitive to season. Therefore temperature interpolation can be carried out on a seasonal or monthly base. Other essential predictors are required to be added to improve the accuracy of the model. Due to the variability of terrain and environmental condition over such a large area, temperature interpolation can be performed separately in different regions: western, central and eastern US. The temperatures interpolated in a modified model in the future can be used as background data for the study of climate change and the greenhouse effect in recent years in the US.

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References

Aalto, J., Pirinen, P., Heikkinen, J., & Venäläinen, A. (2013). Spatial interpolation of monthly climate data for Finland: comparison the performance of kriging and generalized additive models. *Theoretical and Applied Climatology, 112*, 99–111.
Akaike, H. (1974). A new look at the statistical model identification. *Automatic Control, IEEE Transactions on, 19*, 716–723.
Benavides, R., Montes, F., Rubio, A., & Osoro, K. (2007). Geostatistical modelling of air temperature in a mountainous region of Northern Spain. *Agricultural and Forest Meteorology, 146*, 173–188.
Blunden, J., Arndt, D. S., & Baringer, M. O. (2011). State of the climate in 2010. *Bulletin of the American Meteorological Society, 92*, S1–S236.
Boykoff, M. T., & Boykoff, J. M. (2007). Climate change and journalistic norms: a case-study of US mass-media coverage. *Geoforum, 38*(6), 1190–1204.
Brown, D. P., & Comrie, A. C. (2002). Spatial modeling of winter temperature and precipitation in Arizona and New Mexico, USA. *Climate Research, 22*, 115–128.
Courault, D., & Monestiez, P. (1999). Spatial interpolation of air temperature according to atmospheric circulation patterns in southeast France. *International Journal of Climatology, 19*, 365–378.
Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., et al. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology, 28*, 2031–2064.
Daly, C., Gibson, W. P., Taylor, G. H., Johnson, G. L., & Pasteris, P. (2002). A knowledge-based approach to the statistical mapping of climate. *Climate Research, 22*(2), 99–113.
Di Luzio, M., Johnson, G. L., Daly, C., Eischeid, J. K., & Arnold, J. G. (2008). Constructing retrospective gridded daily precipitation and temperature datasets for the conterminous United States. *Journal of Applied Meteorology and Climatology, 47*, 475–497.
Dodson, R., & Marks, D. (1997). Daily air temperature interpolated at high spatial resolution over a large mountainous region. *Climate Research, 8*, 1–20.
Dryas, I., & Ustrnul, Z. (2007). The spatial analysis of the selected meteorological fields in the example of Poland. In H. Dobesch, et al. (Eds.), *Spatial interpolation for climate data: The use of GIS in climatology and meteorology* (pp. 87–96). London: ISTE Ltd.
Duncan, J., & Biggs, E. M. (2012). Assessing the accuracy and applied use of satellite-derived precipitation estimates over Nepal. *Applied Geography, 34*, 626–638.
Geary, R. C. (1954). The contiguity ratio and statistical mapping. *The Incorporated Statistician, 5*, 115–145.
Hattis, D., Ogneva-Himmelberger, Y., & Ratick, S. (2012). The spatial variability of heat-related mortality in Massachusetts. *Applied Geography, 33*, 45–52.
Holdaway, M. R. (1996). Spatial modeling and interpolation of monthly temperature using kriging. *Climate Research, 6*, 215–225.
Hudson, G., & Wackernagel, H. (1994). Mapping temperature using kriging with external drift: theory and an example from Scotland. *International Journal of Climatology, 14*, 77–91.
Hunter, R. D., & Meentemeyer, R. K. (2005). Climatologically aided mapping of daily precipitation and temperature. *Journal of Applied Meteorology, 44*, 1501–1510.
Kurtzman, D., & Kadmon, R. (1999). Mapping of temperature variables in Israel: a comparison of different interpolation methods. *Climate Research, 13*, 33–43.
Liao, S. B., & Li, Z. H. (2004). Some practical problems related to rasterization of air temperature. *Meteorological Science and Technology, 5*, 352–356.
Li, X., Cheng, G., & Lu, L. (2005). Spatial analysis of air temperature in the Qinghai-Tibet Plateau. *Arctic, Antarctic, and Alpine Research, 37*, 246–252.
Li, S., Xie, Y., Brown, D. G., Bai, Y., Hua, J., & Judd, K. (2013). Spatial variability of the adaptation of grassland vegetation to climatic change in Inner Mongolia of China. *Applied Geography, 43*, 1–12.

Mahdian, M. H., Bandarabady, S. R., Sokouti, R., & Banis, Y. N. (2009). Appraisal of the geostatistical methods to estimate monthly and annual temperature. *Journal of Applied Sciences, 9*, 128–134.

Minder, J. R., Mote, P. W., & Lundquist, J. D. (2010). Surface temperature lapse rates over complex terrain: lessons from the Cascade Mountains. *Journal of Geophysical Research, 115*(D14), D14122.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*, 17–23.

NOAA National Climatic Data Center. State of the climate: national overview for annual 2010. published online December 2010, retrieved on July 9, 2013 from http://www.ncdc.noaa.gov/sotc/national/2010/13.

NCDC. (2010a). GHCN-monthly version 3 national oceanic and atmospheric administration. http://www.ncdc.noaa.gov/ghcnm/v3.php.

NCDC. (2010b). Monthly summary data on the state/divisional level in the U.S. ftp://ftp.ncdc.noaa.gov/pub/data/cirs/drd964x.tmp.txt.

Qi, X., Wei, L., Barker, L., Lekiachvili, A., & Zhang, X. (2012). Comparison of ArcGIS and SAS geostatistical analyst to estimate population-weighted monthly temperature for US counties. *Journal of Resources and Ecology, 3*(3), 220–229.

Rolland, C. (2003). Spatial and seasonal variations of air temperature lapse rates in Alpine regions. *Journal of Climate, 16*, 1032–1046.

Samanta, S., Pal, D. K., Lohar, D., & Pal, B. (2012). Interpolation of climate variables and temperature modeling. *Theoretical and Applied Climatology, 107*, 35–45.

Serbin, S. P., & Kucharik, C. J. (2009). Spatiotemporal mapping of temperature and precipitation for the development of a multidecadal climatic dataset for Wisconsin. *Journal of Applied Meteorology and Climatology, 48*, 742–757.

Silberman, J. A., & Rees, P. W. (2010). Reinventing mountain settlements: a GIS model for identifying possible ski towns in the US Rocky Mountains. *Applied Geography, 30*(1), 36–49.

Sluiter, R. (2009). *Interpolation methods for climate data-literature review*. KNMI intern rapport. De Bilt: Royal Netherlands Meteorological Institute.

Stahl, K., Moore, R. D., Floyer, J. A., Asplin, M. G., & McKendry, I. G. (2006). Comparison of approaches for spatial interpolation of daily air temperature in a large region with complex topography and highly variable station density. *Agricultural and Forest Meteorology, 139*, 224–236.

Trisurat, Y., Shrestha, R. P., & Kjelgren, R. (2011). Plant species vulnerability to climate change in Peninsular Thailand. *Applied Geography, 31*(3), 1106–1114.

Valeriano, M. M., & Rossetti, D. F. (2012). Topodata: Brazilian full coverage refinement of SRTM data. *Applied Geography, 32*(2), 300–309.

van der Veer, G., Voerkelius, S., Lorentz, G., Heiss, G., & Hoogewerff, J. A. (2009). Spatial interpolation of the deuterium and oxygen-18 composition of global precipitation using temperature as ancillary variable. *Journal of Geochemical Exploration, 101*(2), 175–184.

Volin, J. C., Liu, Z., Higer, A., Mazzotti, F., Owen, D., Allen, J., et al. (2008). Validation of a spatially continuous EDEN water-surface model for the everglades, Florida. *Department of Natural Resources and The Environment Articles*, 8.

Wang, K., Zhang, C., & Li, W. (2013). Predictive mapping of soil total nitrogen at a regional scale: a comparison between geographically weighted regression and cokriging. *Applied Geography, 42*, 73–85.

Willmott, C. J. (1981). On the validation of models. *Physical Geography, 2*, 184–194.

Willmott, C. J., & Matsuura, K. (1995). Smart interpolation of annually averaged air temperature in the United States. *Journal of Applied Meteorology, 34*, 2577–2586.

Yang, J. S., Wang, Y. Q., & August, P. V. (2004). Estimation of land surface temperature using spatial interpolation and satellite-derived surface emissivity. *Journal of Environmental Informatics, 4*, 37–44.

Yunus, F., Jaafar, J., Mahmud, Z., Shafie, A., & Idris, R. (2012). Role of environmental factors in modeling of air temperature element in peninsular Malaysia. *System Engineering and Technology (ICSET), International Conference on IEEE*, 1–6.

Zhao, C. Y., Nan, Z. R., & Cheng, G. D. (2005). Methods for modeling of temporal and spatial distribution of air temperature at landscape scale in the southern Qilian mountains, China. *Ecological Modelling, 189*, 209–220.