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Geostatistical Modeling of Air Temperature Using Thermal Remote Sensing

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Abstract: Geographic Information Systems and spatial interpolation are the most often used geographic sciences for spatial analysis and visualization of temperature to use in hydrological studies. According to dependency of nature of thermal bands data to temperature, using thermal remote sensing images as auxiliary data can be useful in air temperature spatial interpolation. In light of these considerations, we used Landsat thermal bands together with Kriging and Co-kriging geostatistical methods for four seasons to interpolate mean temperature in Northeast of Iran as a region with low density of gauge distribution. Using Landsat (instead of for instance MODIS) is firstly to provide requirement of mentioned science. Secondly, help to provide deeper understand in case of "climatic neighborhood" concept. To assess the efficiency of the method cross validation indicators were used. Thermal images used in this study increase the accuracy for the winter and autumn in comparison to unused outputs. The provided results for spring and summer were good too. Also, the spatial impacts of thermal images on the results of autumn and spring are significant. This research indicated that using thermal images as auxiliary data have potential to improve spatial prediction accuracy and quality. At the end, we know that number of our observation stations are too low and considering the Kriging requirements like normal distribution and stationarity is toilsome but we should consider that this problem exist in the regions with low density of gauges and should find a way to enhance the air temperature interpolation in these cases.

Keywords: Interpolation, Kriging, Thermal Co-Kriging, Golestan, Environmental Studies

1. Introduction

A valuable source of information can be provided by remotely sensed data that helping to understand spatial facts and providing authorities and scholars with genuine data sources for better decision making [7]. "Thermal remote sensing is the branch of remote sensing that deals with the acquisition, processing and interpretation of data acquired primarily in the thermal infrared (TIR) region of the electromagnetic (EM) spectrum" [16].

One of the most often used geographic techniques is spatial interpolation. It used for spatial query of properties, spatial data visualization and help to spatial decision-making processes in geography, earth sciences, and environmental science [12]. Indeed, spatial interpolation is often used to calculate a value of an unknown quantity at unmeasured locations with the available measurements at sampled sites" [9], [12]. Moreover, the spatial interpolation also applies for temperature mapping. For land evaluation and characterization systems in hydrological and ecological models, air temperature is one of the input variables [2]. Benavides et al. 2007 and some others e.g. [10] believe that modeling air temperature in topographically rough regions is a challenge and it is strict to obtain accurate climatic maps.

Different spatial interpolation methods have been used to model air temperature; the more recently geostatistical models in continuation of former methods like regression analysis, thin-plate smoothing splines (ANUSPLIN), inverse distance interpolation weighting or Voronoi tessellation [2], [17]. The addition of auxiliary variables is often believed to increase the performance of spatial prediction [12]. Some auxiliary variables that used hole around the world by researchers are Digital Elevation Model (DEM), slope, aspect, distance to sea, solar radiation, land cover, NDVI and etc [2], [3], [6], [11]. In this regard, due to development of remote sensing satellites and providing thermal images we decided to use thermal band of Landsat to enhance the performance of temperature interpolation.

In other word, this study aimed to use Geostatistics and thermal remote sensing bands as an ancillary data to spatially predict mean air temperature in four season winter (March), spring (May), summer (August) and autumn (November) in a complex topographic region of North-east of Iran.

2. Material and Method

2.1. Study Area

Study area is located in the northeastern part of Iran and covers an area of 18000 km^2 (Figure. 1). It is located between the latitude of 36°43’ and 38°07’N and the longitude of 54°19’ and 56°27’E. It included most of Gorganrood watershed and parts of Atrak and Gharasoo watersheds [13]. The altitude range is between -30 to 2956 meters above sea level. This region is very important in viewpoint of agricultural production and some parts of it are under impacts of yearly floods. It has a remarkable climate variation: the southern band which is covered by dense forests and croplands is humid and the northern parts are semi-arid and arid [5], [14].

2.2. Data Sets

Two categories of data were used in this research: mean air temperature data as station points and Remote Sensing images as raster. In the case of temperature data there are 27 meteorological stations with different time periods in the area. But according to the definition of the World Meteorological Organization (WMO), data for a 30-year period are recommended because they provide stable and reproducible monthly means [2]. Therefore, monthly mean air temperature data for November 1988, August 1999, May 2000 and March 2009 of eight stations, were selected (Table 1; Figure. 1). Unlike many researches that only investigate the temperature interpolation in the coldest and warmest month we used thermal bands of four cloud free Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) images (path 162, row 34) for March of 2009, May of 2000, August of 1999 and November of 1988 on behalf of four season (Figure. 2 and 3). TM and ETM+ sensor thermal bands are in the 10.40-12.50 µm with spatial resolution of 120/60 m [18]. It is essential to mention that, both high gain and low gain thermal of August 1999 ETM+ images were used in the interpolation process. The images were selected and downloaded from the United States Geological Survey’s (USGS) National Center for Earth Resources Observation and Science (http://glovis.usgs.gov).

Table 1. *Meteorological Stations.*

Station	Latitude	Longitude	Elevation(m)
Tamar	37° 29´	55° 30´	132
Gonbad	37° 14´	55° 09´	36
Araz Kuse	37° 13´	55° 08´	34
Bhalke Dashli	37° 04´	54° 47´	24
Fazel Abad	37° 54´	54° 45´	210
Sad Gorgan	37° 12´	54° 44´	12
Ghafar Haji	37° 00´	54° 08´	-22
Cheshme Khan	37° 18´	56° 07´	1250
Robat Gharabil	37° 21´	56° 18´	1450

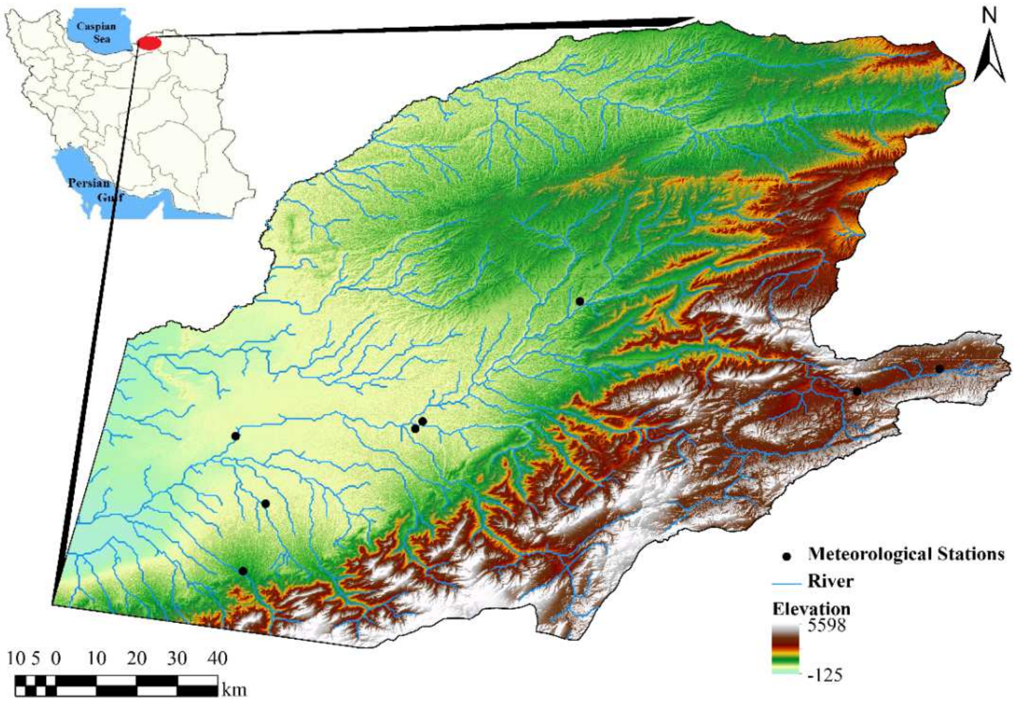

Figure 1. *Location of the study area and meteorological stations.*

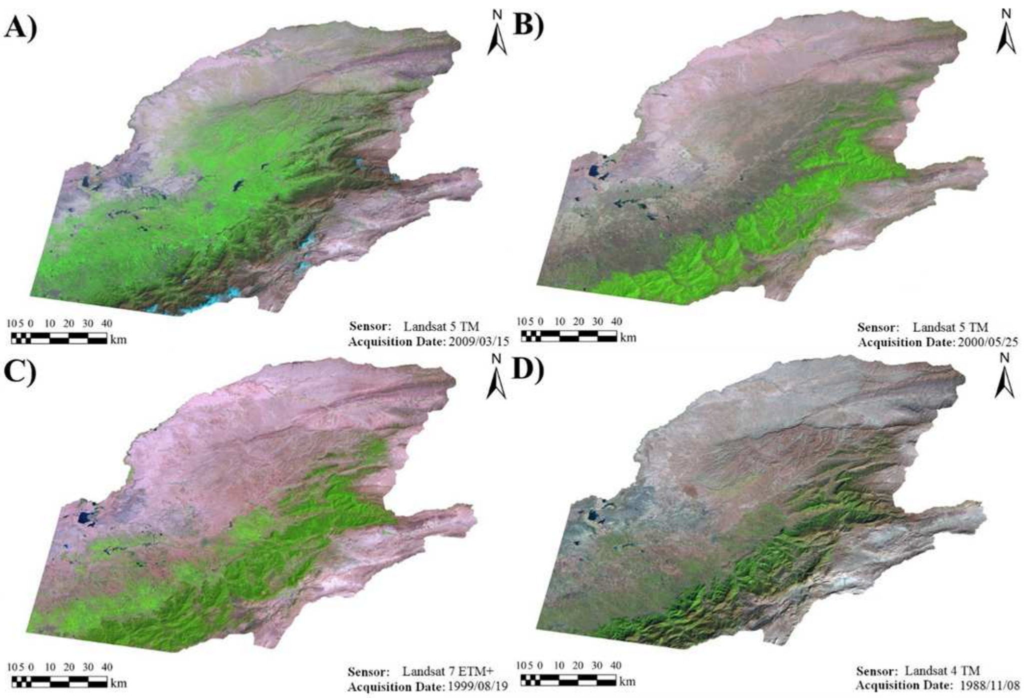

Figure 2. *Satellite images of the study area in A) March, B) May, C) August and D) November.*

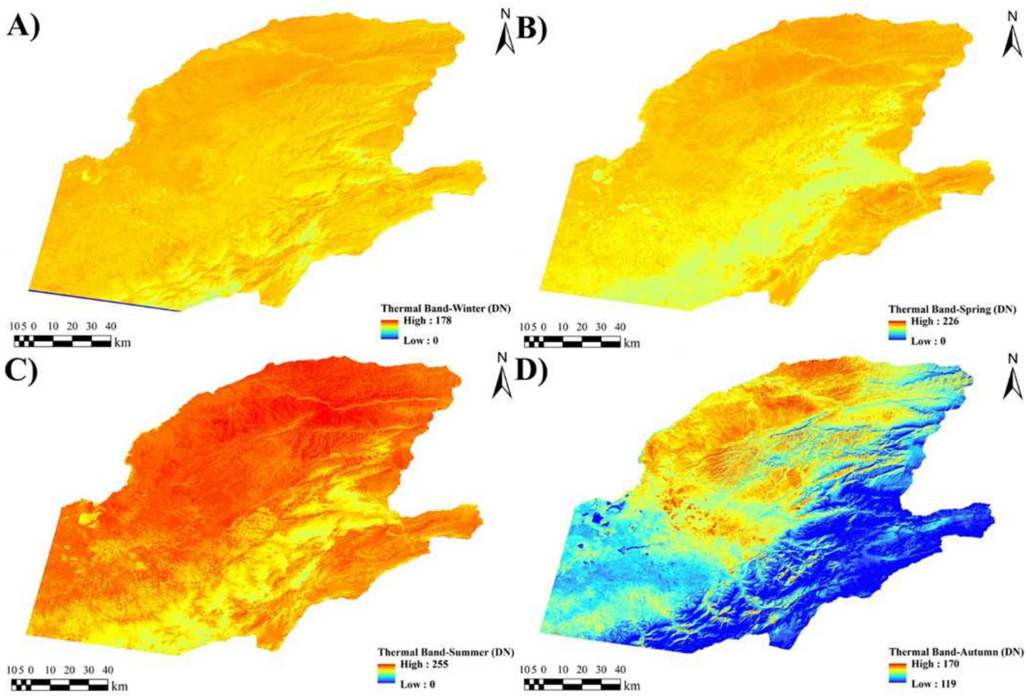

Figure 3. *Satellite images thermal bands of the study area in A) March, B) May, C) August and D) November.*

2.3. Geostatistics: Kriging/Co-Kriging

As a brief description, Kriging is a geostatistical interpolation method derived from regionalized variable theory. It assumes that the distance, the direction, or both between observations which show spatial correlation can be employed to explain variation in the surface [4]. Kriging can propose the finest linear unbiased estimates with an accurate description of the spatial structure of the data and valuable information about estimation error distributions [4], [15]. "A clear improvement to ordinary space–time kriging includes the use of ancillary data to aid in the estimation process, referred to as external drift" [20]. Cokriging is a versatile statistical approach for spatial point estimation, especially, when both primary and auxiliary attributes are available. If each component of $z(s_0)$ satisfies the intrinsic hypothesis that assumes that stationarity of the differences between pairs of data points exists in the first and second moments, then co-kriging is unbiased and defined by equations 1, 2, and 3 [11],

[12].

$$\hat{z}(s_0) = \sum_{j=1}^{n} z(s_j)\Lambda_{j\bullet} \tag{1}$$

$$\sum_{j=1}^{n} \Lambda_{j\bullet} = I \tag{2}$$

$$\sum_{\emptyset=1}^{v} \Gamma(s_i, s_j) + \Psi = \Gamma(s_i, s_0)\ i = 1, \dots, n \tag{3}$$

Where I is an identity matrix = [1, 0, …, 0]^T, T indicates a transpose, and $\Lambda_{j\bullet}$ are the weights associated with the prediction. $z(s_j)$ is the vector $z_1(s_j)\dots z_m(s_j)$. $\Gamma(s_i,s_j)$ and $\Gamma(s_i,s_0)$ are the cross variograms and Ψ is the Lagrange Multiplier for i from 1 to n [11], [12].

The ordinary and simple kriging and co-kriging with and without transformations, optimization and stable model were implemented and tested and the results of them were compared to select the best output of anyone.

2.4. Validation and Comparison

A commonly applied method for accuracy assessment in Geostatistics is the leave-one-out cross-validation because no reserved data are required for the data validation [2]. In other word, as the number of sampled sites is usually not very large and they are sparse throughout the study area, so all the sampled data are used for the spatial prediction in order to improve the precision of the predictions [2]. In this regards, results were compared by goodness-of fit statistics such as Mean Error (ME), Root Mean Square Error (RMSE), Mean Standardized Error (MSE), Average Standard Error (ASE) and Root Mean Square Standardized Error (RMSSE) [1], [2], [4], [5], [12], [19].

$$ME = \frac{1}{n}\sum_{i=1}^{n}[Z(x_i) - Z'(x_i)] \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[Z\,(x_i) - Z'(x_i)]^2} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}[Z(x_i) - Z'(x_i)]/\sigma(x_i)}{n} \tag{6}$$

$$ASE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[Z'(x_i) - \sum_{i=1}^{n} Z'(x_i)/n]^2} \tag{7}$$

$$RMSSE = \frac{1}{n}\sum_{i=1}^{n}[Z_1(x_i) - Z_2(x_i)]^{\,2} \tag{8}$$

Where $Z\,(x_i)$ is the measured value of the sample points, and its fitted values is $Z'(x_i)$; Standard value of them is $Z_1(x_i)$ and $Z_2(x_i)$ respectively and $\sigma(x_i)$ is standard deviation [1], [8], [19].

The ME indicates whether the model is, on average, producing estimates that are overestimating or underestimating the observed values. In a well-adapted model, ME and SME should be close to zero for unbiased methods. The RMSE measure the average precision of the prediction and should be as small as possible. The model that performs the best will be the one with the smallest RMSE. This would suggest that the predictions are impartial and close to the respective real values. The values of ASE are used in order to evaluate the prediction divergence from real values. Therefore, ASE should be the same as RMSE, in order to evaluate the divergence of predictions correctly. The values of RMSSE should be close to 1. If the RMSSE are greater than 1, then the variability of the predictions is underestimated vice versa [1], [8], [19].

The ME, RMSE, ASE, SME and RMSSE were calculated to check the performance of each state of interpolations. Therefore, results based on described above rules was compared.

3. Result and Discussion

In this study, due to low density of meteorological stations, we used the thermal bands of remote sensing imageries from Landsat. Figures 4 and 5 show four maps of winter to autumn predicted mean temperature derived from Kriging and Thermal Co-Kriging (TCK). Kriging shows interior regions warm while, there are two warm areas in the center and west (plains to the coastal area) in the TCK output. In spring and summer both of them has the same trend and the warm area is in the center (plain) and for the summer warm area move somehow to the west (to the coast). In the autumn the kriging shows a descending gradual from west to east but in the TCK warm area located in the north part of the region (hills) with some spatial distribution. On the other hand, the cool parts in all seasons are in the east part of the study area (mountains) and spread over the north and an area in the west in spring.

Comparing statistics in the table 2 shows the difference between main data, kriging and TCK. In Min the difference between TCK and main data in winter, spring and autumn is less than kriging but in the summer the kriging is closer to the main data. While, For the Max kriging is more similar to the main data in winter, spring and autumn and for the summer the TCK is closer. The winter, spring and summer for the kriging and autumn for the TCK are closer to the main data in the Mean parameter. In the S.D. variable winter and autumn for TCK and spring and summer for kriging are more similar to the main data.

Table 2. *Statistics of the predicted temperatures.*

Geostatistics Method	Winter	Spring	Summer	Autumn
Main Data				
Min	6.1	16.5	22.9	10.3
Max	13.2	22.8	31.2	18
Mean	10.87	19.8	27.76	15.18
S.D.	2.91	2.26	3.14	2.73
Kriging				
Min	6.62	16.41	23.11	12.24
Max	12.87	22.85	32.76	16.68
Mean	10.86	19.53	27.84	14.87
S.D.	1.69	1.54	3.00	1.34
Thermal Co-Kriging				
Min	6.094	16.49	23.24	10.63
Max	14.68	23.20	31.24	19.60
Mean	11.08	19.43	27.59	14.97
S.D.	2.12	1.40	2	1.55

Evaluation results based on ME, RMSE, MSE, RMSSE and ASE as goodness-of fit statistics can be seen in Table 3.

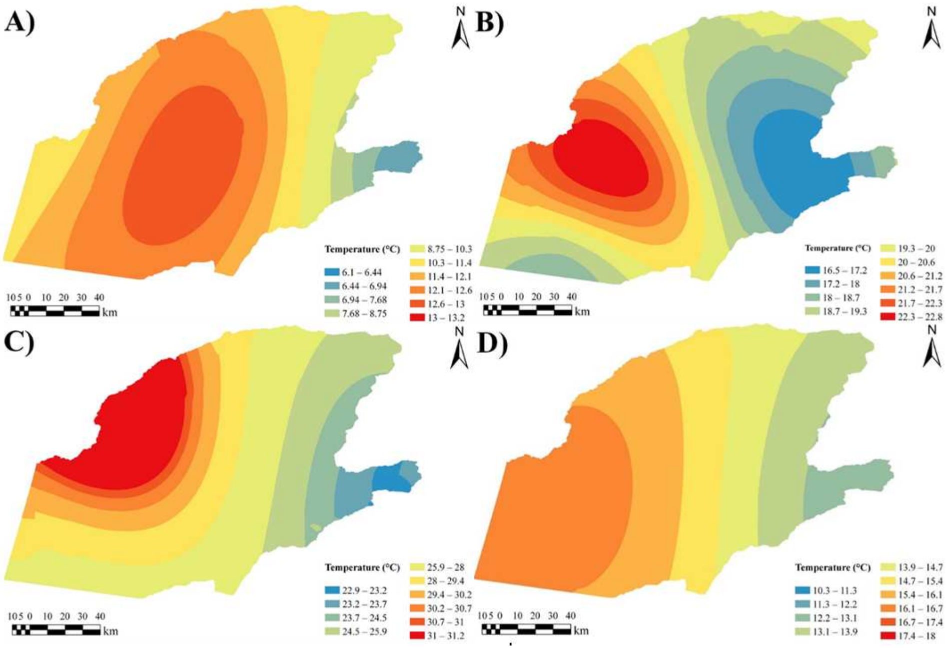

Figure 4. *Models of predicted mean air temperature for Kriging: (A) winter, (B) spring, (C) summer, (D) autumn.*

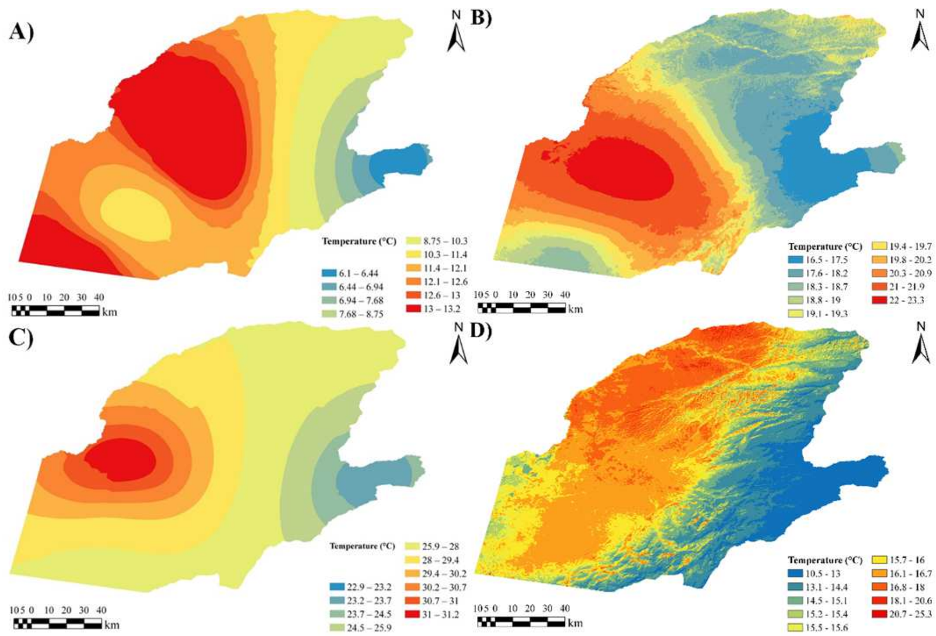

Figure 5. *Models of predicted mean air temperature with TCK: (A) winter, (B) spring, (C) summer, (D) autumn.*

Table 3. *Results of ME, RMSE, MSE, RMSSE and ASE.*

Geostatistics Method	Winter	Spring	Summer	Autumn
Kriging				
ME	0.0004	0.295	-0.128	0.042
RMSE	1.371	1.005	1.403	2.036
MSE	0.005	0.135	-0.3049	0.007
ASE	2.127	1.330	1.490	2.140
RMSSE	0.703	0.795	1.019	0.948
Thermal Co-Kriging				
ME	-0.133	0.24	-0.039	0.11
RMSE	1.083	1.043	1.475	1.902
MSE	-0.026	0.102	0.002	0.051
ASE	1.686	1.266	1.778	2.11
RMSSE	0.952	0.863	0.927	0.902

For optimality and validity of the models if the root-mean-squared prediction error is smaller for a particular model therefore it is the optimal model. However, when comparing to another model, the root-mean-squared prediction error may be closer to the average estimated prediction standard error. This is a more valid model, because when we predict at a point without data, we have only the estimated standard errors to assess our uncertainty of that prediction. We also must check that the root-mean-square standardized is close to one [1]. In light of these considerations and as can be understood from Table 3, TCK is optimal for the winter and autumn and valid for the winter and kriging is optimal for spring and summer and valid for summer. Also it has to be emphasized that, in general inspections of the results TCK getting more score in the winter and spring and kriging in summer and autumn. Furthermore, spatial distribution of standard errors maps for kriging and TCK are shown in Figures 6 and 7.

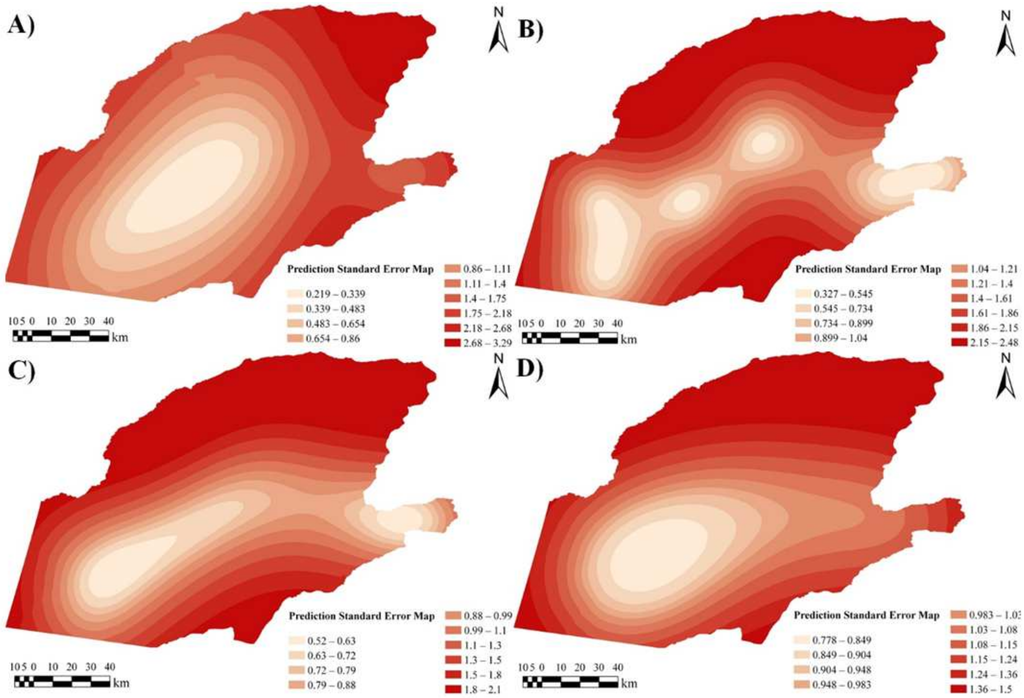

Figure 6. *Standard errors map of mean air temperature with Kriging: (A) winter, (B) spring, (C) summer, (D) autumn.*

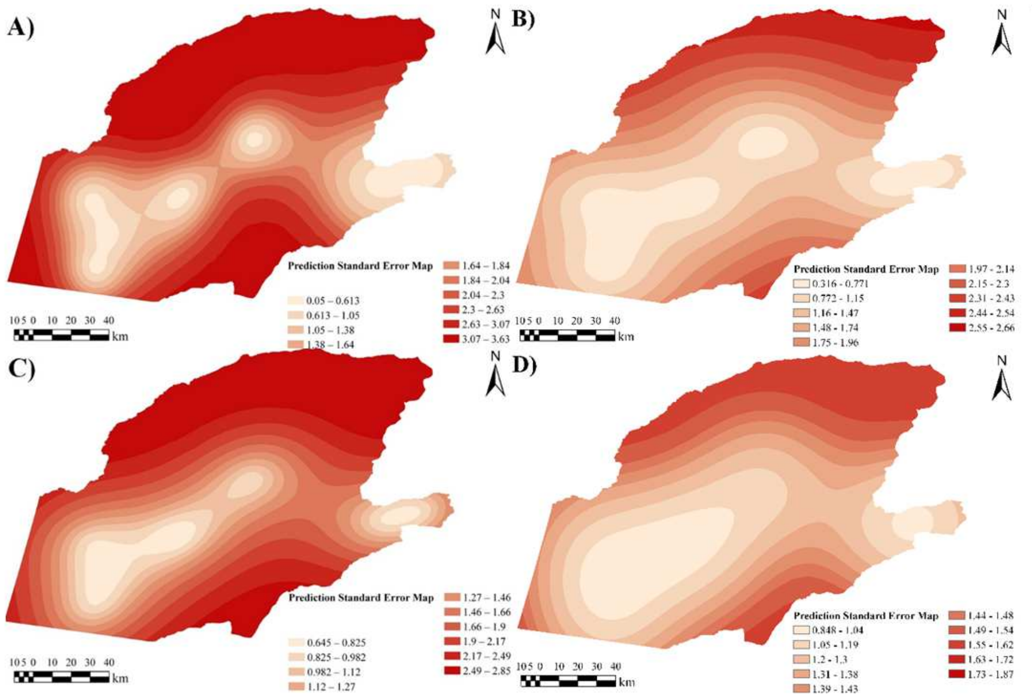

Figure 7. *Standard errors maps of mean air temperature with Thermal Co-Kriging: (A) winter, (B) spring, (C) summer, (D) autumn.*

4. Conclusions and Future Works

Developing Remote Sensing data (including thermal bands) is taking place at an unprecedented rate nowadays. In line with this development, satellite images can be relatively easily in access. Owing to this we decided to use the thermal bands of the TM and ETM+ sensors as auxiliary data to enhance the mean temperature interpolation quality in the complex regions with less meteorological stations. This study reveals that, for this region with mentioned images the TCK has shown good performance for winter and autumn instead of kriging, though its result for the spring and summer is good too. Future direction of this research include testing and use of different spatial interpolations and Geostatistics methods, thermal bands for different regions and time periods. It is recommended to provide thermal inputs of Geostatistics methods using different sampling methods to reduce calculation volumes. Furthermore, check the usefulness of the method for other geographical factors that need to be interpolated.

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