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Comparison of Different Interpolation Techniques for Modelling Temperatures in Middle Black Sea Region

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Abstract: Objective of this study was to determine the best method for modelling and mapping monthly and annual temperatures (minimum, maximum, mean) of Middle Black Sea Region by geographical information systems (GIS). Data from 72 different meteorological observation stations were used for modelling and mapping. Inverse Distance Weighting (IDW), Thin-plate Smoothing Spline (TPS), Simple Kriging (SK), Cokriging (CK) and Multiple Linear Regression (MLR) methods were used to analyze spatial distribution of temperature data. Correlation coefficients among the estimated and measured monthly mean temperatures varied between 0.80 and 0.95. Correlation coefficients for all months were found to be significant ($P < 0.01$). In general, MLR yielded the best results for monthly mean temperatures. While TPS was identified as the best method for monthly minimum temperatures for most of the months, MLR, IDW, and CK methods yielded best results for other months. All methods yielded unsatisfactory results for maximum temperatures, especially for summer months.

Key words: IDW; Multiple Linear Regression; Simple Kriging; Temperature; Thin-plate Smoothing Spline

1. Introduction

Climate variables exhibit large variations over short distances especially in complex topographies and are influenced by several external factors such as vegetation, water surface, altitude, etc. In fact, such parameters should be observed with a sufficient meteorological station network. In general, more accurate and reliable data are available in developed countries owing to intensive meteorological observation stations compared to developing countries.

Spatially continuous data play a significant role in environmental sciences. Environmental managers usually require spatially continuous data over the region of interest to make effective and confident decisions, and scientists need accurate spatially continuous data across a region to make justified interpretations (e.g. Susam et al. 2006; Doğan et al. 2013). Such data are, however, usually not always readily available and often difficult and expensive to acquire, especially for mountainous or deep marine regions. Moreover, environmental data collected from field surveys are often from point sources. Thus, the values of an attribute at unsampled points should be estimated in order to generate spatially continuous data. In such instances, spatial interpolation methods provide a tool for estimating the values of an environmental variable at unsampled sites using data from point of observations (Li and Heap 2011).

The spatial distribution of the data obtained from a point is more effective and useful than the simple averages between the sample points. Considering the variations among the data points, an appropriate method should be selected for interpolations (Burrough and McDonnell 1998). Such selection is more critical in mountainous terrains where the data cannot be collected frequently (Collins and Bolstad 1996). Most of the interpolation methods yield similar results in cases with sufficient data, but assumptions made in cases with insufficient data may cause significant differences among the methods. Therefore, selection of most appropriate interpolation method becomes the critical issue (Burrough and McDonnell 1998).

Researchers in agriculture and forestry are most of the time not able to access sufficient and reliable data. Therefore, they tend to use of much easier but very general solutions like linear relationships between the parameters. Another simple approach is to identify the closest meteorological station for each location by using Thiessen polygon method. However, a complex methodology is needed for mountainous terrains over where climate variables show significant variations in short intervals. Such methodology should involve high resolution climate data layers showing the spatially continuous surfaces and also include new approaches for sufficient and reliable results especially in the agricultural and forestry research and implementation.

Interpolation was applied in production of spatially continuous climate data (Türkeş et al. 2002; Guan et al. 2009; Ashiq et al. 2010; Demircan et al. 2011; Yavuz and Hüseyin 2012; Doğru et al. 2013; Güler and Kara 2014). Among the interpolation methods, kriging methods were proven to yield best results in several studies (Skirvin et al. 2003; Yavuz and Hüseyin 2012; Güler and Kara 2014). Especially Cokriging method taking the elevations as secondary variables into consideration provides better outcomes. Success of the method mostly depends on the level of correlation between the climate parameter and elevations. Other Kriging methods like Ordinary Kriging (OK) are selected in cases with low level of correlation between climate parameters and elevation (Daly et al. 1994).

Regression methods are used for interpolation of climate variables in several studies. In regions where climate parameters have a significant correlation with the topography, the position of the station and elevation are usually considered as independent variables (Kurtzman and Kadmon 1999; Ninyerola et al. 2000; Antonic et al. 2001; Marquínez et al. 2003; Skirvin et al. 2003; Güler et al. 2007; Güler and Kara 2014). Depending on their influence on climatic parameters, independent variables such as solar radiation and cloudiness can also be included in Multiple Linear Regression (MLR) (Ninyerola et al. 2000). While different interpolation methods were comparatively used and the best one for each region was selected in some studies (Daly et al. 1994; Kurtzman and Kadmon 1999; Skirvin et al. 2003; Spadavecchia and Williams 2009), only one method (particularly MLR) was used in some others (Ninyerola et al. 2000; Antonic et al. 2001; Marquínez et al. 2003; Güler et al. 2007; Moral 2010).

Several factors may influence the performance of spatial interpolation methods. These include; sampling density (Isaaks and Srivastava 1989; Burrough and McDonnell 1998; Stahl et al. 2006), sample spatial distribution (Collins and Bolstad 1996), sample clustering (Isaaks and Srivastava 1989), surface type (Voltz and Webster 1990), data variance (Martínez-Cob 1996), data normality (Rossi et al. 1992), quality of secondary information (Martínez-Cob 1996; Goovaerts 1997; Wang et al. 2005; Hengl 2007) stratification (Voltz and Webster 1990), and grid size or resolution (Hengl 2007).

In this study, IDW, TPS, SK, CK and MLR methodologies were used to map monthly mean, minimum, and maximum temperatures of Middle Black Sea Region. The objective was to evaluate the potential use of such methods for modelling and mapping the temperatures in this region, characterized by a wide range of topographic and climatic characteristics. Particularly, a key part of this work is concerned with the identification topography-related external variables able to account for part of the observed temperature spatial variability and, then, useful to improve the reliability of the interpolation methods.

2. Material and Methods

2.1. Study region and dataset

The study was conducted in a 62219 km^2 area in northern Turkey. The study area and distribution of stations used in this study are shown in Fig. 1. The majority of the study area is mountainous, with small patches of plains. Particularly in the southern part of the area, extreme topographic changes are prominent over short distances, gradually decreasing from coast to inland. Elevation in the study area ranges from zero to 2990 m, and the elevation of stations ranges from 4 m to 1300 m.

The area experiences moderate precipitation, ranging from a low of 15 mm in the summer to a high of 70 mm in the autumn months. Temperatures range from a low of 5.5°C in December to a high of 28.7ºC in August. Monthly relative humidity values varied between 39-81%, with lower values inland and higher values along the coast. During the summer, relative humidity values were low (39-45%) throughout the entire region (MGM 2012).

Climate varies from coast to inland area. The coastal region has a typical Mediterranean climate. But, inland region has continental climate properties. In particular, coastal regions are rich in vegetation. Plains and cultivated fields are covered with vineyards, orchards, meadows. Mountains located in the coastal region are covered with forests. The natural vegetation is steppe in inland areas.

A total of 81 observation stations are present in the study area; however, a number of these stations have been closed. The number and observation period of the stations are as follows: 9 stations for 2-6 years, 24 stations for 7-10 years, 27 stations for 11-20 years, and 21 stations for 21-30 years. When the size and current condition of the study area are considered, the need for observed information at sufficient number of points and the observation periods used in previous similar studies, a 7-year cut-off point was determined, and those observation stations with less than seven years of measured values were not used in this study. Accordingly, the study utilized long-term monthly average, minimum, and maximum temperature data obtained from 72 stations with observation periods ranging from 7-30 years. Observation period is between 1975 and 2004.

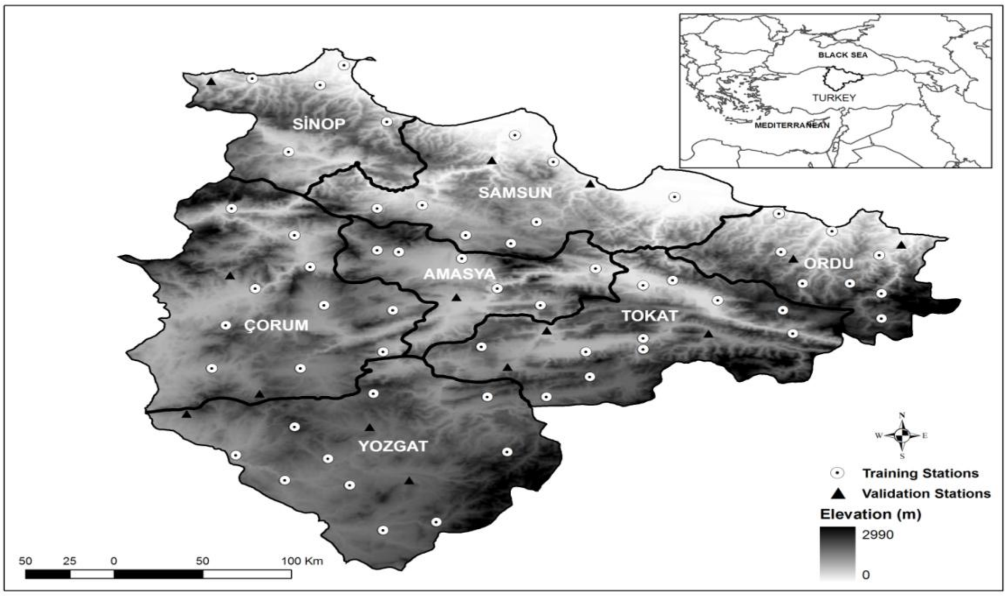

Figure 1. *Map showing the study area and the distribution of meteorological observation stations*

2.2. Spatial interpolation methods

Spatial interpolation entails the use of mathematical models to simulate temperature information at unmeasured points. Among the various models that exist, this study examined two deterministic methods – Inverse Distance Weighting (IDW) and Spline modelling – and two stochastic methods – Simple Kriging and

Cokriging– as well as Multiple Linear Regression. Interpolation was performed in line with Isaaks and Srivastava (1989), Goovaerts (1997), Webster and Oliver (2001) and Wackernagel (2003). In the present study, temperature values were defined as dependent variables and longitude (A), latitude (B), elevation (C), slope (D), exposure (E), distance from sea (F), distance from stream (G), sub-basin elevation (H) and sub-basin slope (I) were defined as independent variables in the regression model. The function also included the following combinations of independent variables: A^2, B^2, AxB, C^2, D^2, E^2, F^2, G^2, H^2, I^2. Similar studies have also used combinations of these factors in regression models (Kurtzman and Kadmon 1999; Marquínez et al. 2003). Multicollinearity between these variables was investigated. Multicollinearity can be investigated based on variance inflation factor values (VIF). Threshold value of VIF is 5. As a results of analyse, all VIF values were highly above 5 except slope (D) and D^2 (VIF=3.28), exposure (E) and E^2 (VIF=1.45), distance from stream (G) and G^2 (VIF=2.82). After calculated VIF, E^2, G^2, D^2 were removed from regression analyses and were looked at r^2 values. But there were not any changes between previous results and new ones. So it was decided to use all independent variables in MLR models. Independent variables used in the MLR model were determined by stepwise selection. Cokriging takes secondary information into account using a cross-variogram between primary and secondary variables. Cokriging usually works well when co-variables are strongly correlated with the primary variable (Goovaerts 1997). In this study, correlation coefficients between temperatures and elevation were significant at $p < 0.01$. Similar to other studies (Goovaerts 1999; Skirvin et al. 2003; Diodato and Ceccarelli 2005), elevation was defined as a co-variable. A digital elevation model was used during the production of independent variables. Data layers were produced using the spatial analysis modules of the ArcGIS 9.2.

2.3. Evaluation procedure

The use of an independent data set is acknowledged to be a more rigorous procedure than crossvalidation. For this reason, the present study used an independent data set to evaluate the results obtained from the models. Different studies have utilized different ratios (Wei et al. 2005: 80%/20%; Ninyerola et al. 2000: 60%/40%; Antonic et al. 2001: 83%/17%; Marquínez et al. 2003: 60%/40%). In the present study, of the 72 available measuring stations, 80% (n=58) were allocated to the training dataset and 20% (n=14) to the evaluation dataset. The locations of the 72 observation station are shown in Fig.1. The triangle-shaped ones were chosen for validation (14 stations) and the round-shaped ones were chosen for training (58 stations).

A number of different techniques may be used to examine the relationship between measured and estimated values in order to determine the most appropriate method among those tested. The performance of an inexact method is frequently evaluated using statistics of differences (absolute and squared) between measured and estimated values at sampled points (Burrough and McDonnell, 1998) such as mean error (ME), mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) (Tellez et al. 2008; Alsamamra et all. 2009; Ruiz-Arias et al, 2011). This study used the correlation coefficient between estimated and observed values to select the most appropriate methods. Correlation values were obtained using the following Equation (Gomez and Gomez 1984);

$$r = \frac{\sum P_i O_i - \frac{\sum P_i \sum O_i}{n}}{\sqrt{\left[\sum P_i^2 - \frac{\left(\sum P_i\right)^2}{n}\right]\left[\sum O_i^2 - \frac{\left(\sum O_i\right)^2}{n}\right]}}$$

Where,
r is the correlation coefficient,
P_i is the estimated value at a specific point,
O_i is the value observed at the same point.

Spatial temperature maps were produced for each month using the method with the highest correlation coefficient for that month.

3. Results and Discussion

3.1. Mean temperature

Correlation coefficients for monthly mean temperatures were given in Table 1. All methods yielded higher coefficients between November and March than the other months with the highest value (0.92-0.95) in December. Decreased *r* values against increased air temperature were observed in summer months. Lowest *r* values were observed (0.45-0.80) in September.

Correlation coefficients of the most appropriate methods (Table 1) varied between 0.80 and 0.95. While the highest value (0.95) was observed in December, the lowest value (0.80) was seen in September. The correlation coefficients of entire months except August were significant at $p < 0.01$.

Multiple Linear Regression was able to provide more appropriate results in all the months, except January, February and November, while SK was found to be the most appropriate method for January and November and Cokriging for February. Correlation coefficients of regression method were also high in January (0.90), February (0.82) and November (0.90). In general, MLR can be used to produce monthly mean temperature maps of the research site. Fig. 2 presents the estimated mean temperature maps created based on selected method.

A significant improvement was observed in the results of monthly mean temperature values with MLR by using secondary data. Independent variables with high correlation coefficients and included in regression equations were given in the Table 2. Significance level of MLR was 1% for all months. While the lowest regression coefficient (0.82) was observed in monthly mean temperatures of October, the highest value (0.93) was obtained for annual mean temperature (Table 2). Among the variables, elevation (C) was particularly included in the models of all months; the distance from the sea (F) was effective in temperature changes of all months except February, November and December. Sub-waterbasin elevation (H) and slope (I) were included in the function of some months. Inversely proportional relationship was observed between temperature and elevation. Daly et al. (1994) used the similar relationships between temperature and elevation during the development of PRISM (Parameter-elevation Regressions on Independent Slopes Model). Such relationships were also used by other researchers interested in particularly the elevation as well as other topographical factors as secondary data (Agnem and Palutikof 2000; Benavides et al. 2007).

Different results were observed in similar studies carried out for the interpolation of monthly mean temperatures. Ninyerola et al. (2007) used independent variables in MLR and IDW methods and reported the regression method as the most appropriate one for mean temperatures. In another study conducted in Israel, MLR including independent variables such as latitude, longitude and altitude was found to be the most appropriate method for the mean temperature (Kurtzman and Kadmon 1999). Skirvin et al. (2003) conducted a research in Arizona and reported Kriging including elevation as external slope was the best method.

Table 1. *Validation results for monthly mean temperatures. The table shows the correlation coefficients obtained by correlation analysis made between test and analysis data*

Methods	Months												
	January	February	March	April	May	June	July	August	September	October	November	December	Annual
IDW	0.87**	0.86**	0.73**	0.61*	0.51	0.48	0.45	0.49	0.45	0.65*	0.87**	0.92**	0.70**
TPS	0.90**	0.90**	0.76**	0.62*	0.60**	0.58*	0.54*	0.60*	0.60*	0.73**	0.90**	0.94**	0.77**
SK	**0.92****	0.91**	0.73**	0.62*	0.64**	0.57*	0.54*	0.60*	0.57*	0.72**	**0.92****	0.94**	0.78**
CK	0.91**	**0.92****	0.79**	0.64*	0.67**	0.64*	0.61*	0.62*	0.58*	0.75**	0.91**	0.94**	0.82**
MLR	0.90**	0.82**	**0.90****	**0.88****	**0.88****	**0.90****	**0.84****	**0.82***	**0.80****	**0.87****	0.90**	**0.95****	**0.90****

*** and * indicate the significance level of 0.01 and 0.05, respectively*

[1]IDW (Inverse Distance Weighting), TPS (Thin-plate smoothing spline), SK (Simple Kriging), CK (Cokriging), MLR (Multiple Linear Regression)

Table 2. *Results of the multiple linear regression analysis for monthly mean temperatures. Coefficients of independent variables selected by Stepwise approach and included in regression equations as well as regression coefficients of the developed models were shown in the column of the relevant month.*

Indipendet Variables[1]	Months												
	January	February	March	April	May	June	July	August	September	October	November	December	Annual
Constant	.	6.22	6.65	41.41	14.79	19.13	22.62	22.55	18.84	15.06	10.74	3.48	13.2
A*B	-2.40e-11											1.32e-12	
C	-0.006	-0.007	-0.005	-0.004	-0.006	-0.007	-0.005	-0.007	-0.008	-0.005	-0.006	-0.004	-0.005
F			3.50e-05	4.80e-05	6.40e-05	6.78e-05	7.00e-05	6.73e-05	5.71e-05	2.29e-05			3.31e-05
G	4.80e-05								4.38e-05		6.32e-05		4.65e-05
H					0.0009		-0.002	-0.002				-0.002	
I			0.11	0.1									
A^2	-6.50e-11												
B^2				-1.50e-12									
C^2				-8.00e-07		-0.001							
F^2	4.80e-11		-9.10e-11	-1.60e-10	-1.81e-10	-1.70e-10	-1.73e-10	-1.60e-10	-1.34e-10	-5.88e-11			-8.77e-11
G^2		2.90e-09											
H^2			-1.15e-06	-1.06e-06	-9.02e-07					-8.65e-07			-1.12e-06
r^2	0.90**	0.87**	0.88**	0.88**	0.84**	0.89**	0.90**	0.89**	0.87**	0.82**	0.87**	0.91**	0.93**

*** and * indicate the significance level of 0.01 and 0.05, respectively*

[1]A (longitude), B (latitude), C (elevation), F (distance from sea), G (distance from stream), H (sub-basin elevation), I (sub-basin slope), r^2 (regression coefficients)

3.2. Minimum temperature

Validation results revealed lover correlation coefficients for minimum temperatures than for mean temperatures. Correlation coefficients of each method were given in Table 3.

While the significance level for correlation coefficients of MLR was found to be 0.05 in September, the level was 0.01 in other months. Correlation coefficients of the most appropriate methods varied between 0.80 and 0.93 with the minimum value in March and the highest value in January. TPS was the most appropriate method in all the months except for March, May, June, July and August, MLR in June and August, CK in March and July and IDW in May. TPS method also yielded similar correlation coefficients in months for which MLR, CK and IDW were found to be the best. Therefore, TPS can be used for minimum temperatures of all months. Kurtzman and Kadmon (1999) also observed the similar results in Israel for minimum temperatures. However, different results could be achieved in studies conducted in different regions. Spadavecchia and Williams (2009) found that

Kriging with external drift method gave the most appropriate results., Luna et al. (2006) reported that the most appropriate results were obtained from the residual Kriging method which takes elevation into consideration. Ninyerola et al. (2007) indicated the most appropriate method as the regression method using the distance from the sea as an independent variable and the IDW method. Fig. 3 presents the estimated minimum temperature maps created based on selected method.

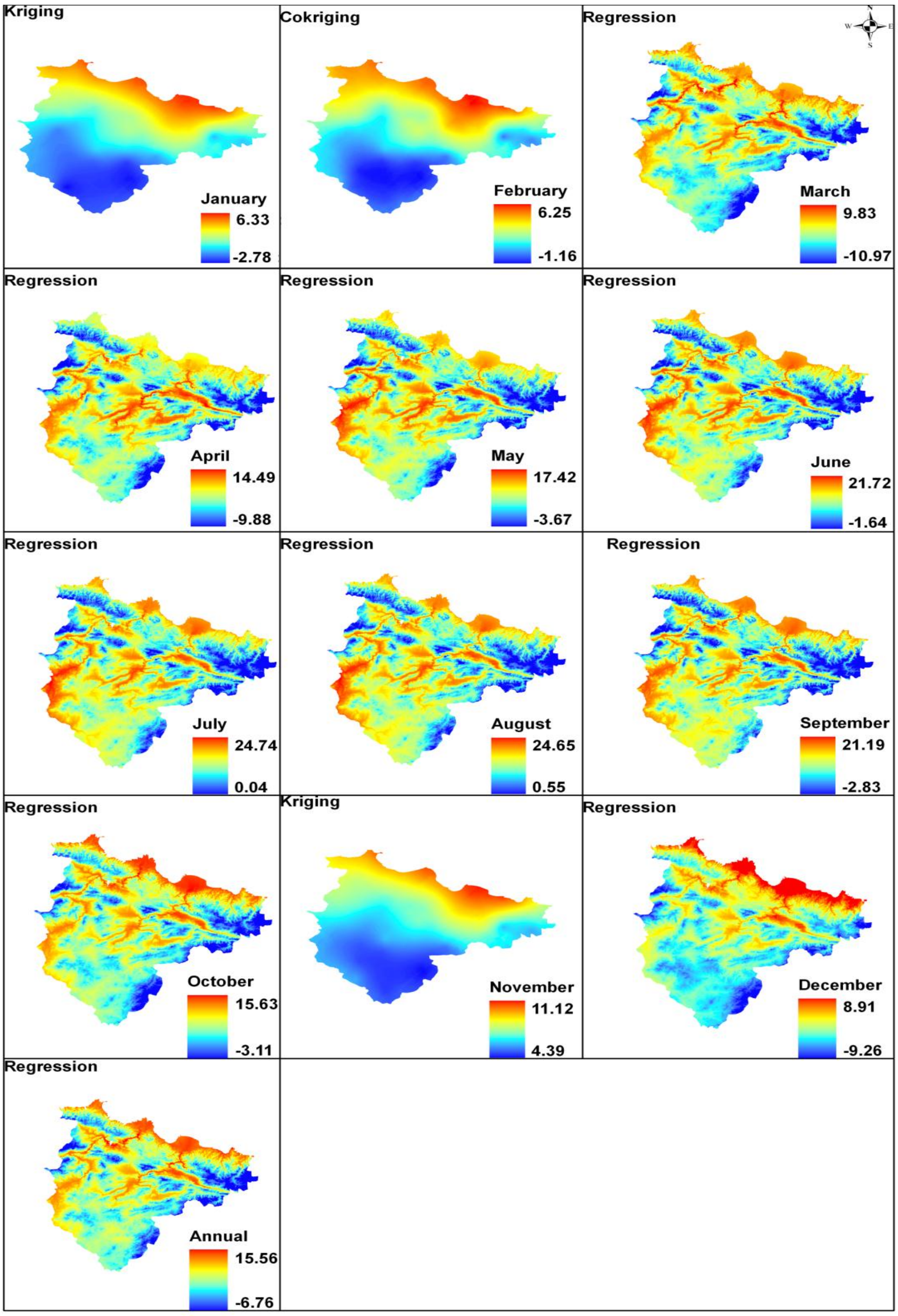

Figure 2. *Monthly mean temperature maps produced by using the most appropriate methods. All values in legends are $^{\circ}$C.*

Table 3. *Validation results for minimum temperatures*

	Months												
Methods[1]	January	February	March	April	May	June	July	August	September	October	November	December	Annual
IDW	0.92**	0.89**	0.75**	0.83**	**0.85****	0.86**	0.76**	0.82**	0.84**	0.84**	0.91**	0.88**	0.91**
TPS	**0.93****	**0.91****	0.78**	**0.84****	0.84**	0.88**	0.78**	0.85**	**0.86****	**0.85****	**0.92****	**0.90****	**0.92****
SK	0.92**	0.90**	0.78**	0.80**	0.81**	0.89**	0.77**	0.83**	0.85**	0.84**	0.90**	0.89**	0.91**
CK	0.92**	0.90**	**0.80****	0.79**	0.81**	0.88**	**0.81****	0.83**	0.85**	0.83**	0.91**	0.88**	0.92**
MLR	0.80**	0.70**	0.71**	0.82**	0.73**	**0.90****	0.80**	**0.86****	0.66*	0.83**	0.90**	0.72**	0.76**

*** and * indicate the significance level of 0.01 and 0.05, respectively*

[1]IDW (Inverse Distance Weighting), TPS (Thin-plate smoothing spline), SK (Simple Kriging), CK (Cokriging), MLR (Multiple Linear Regression)

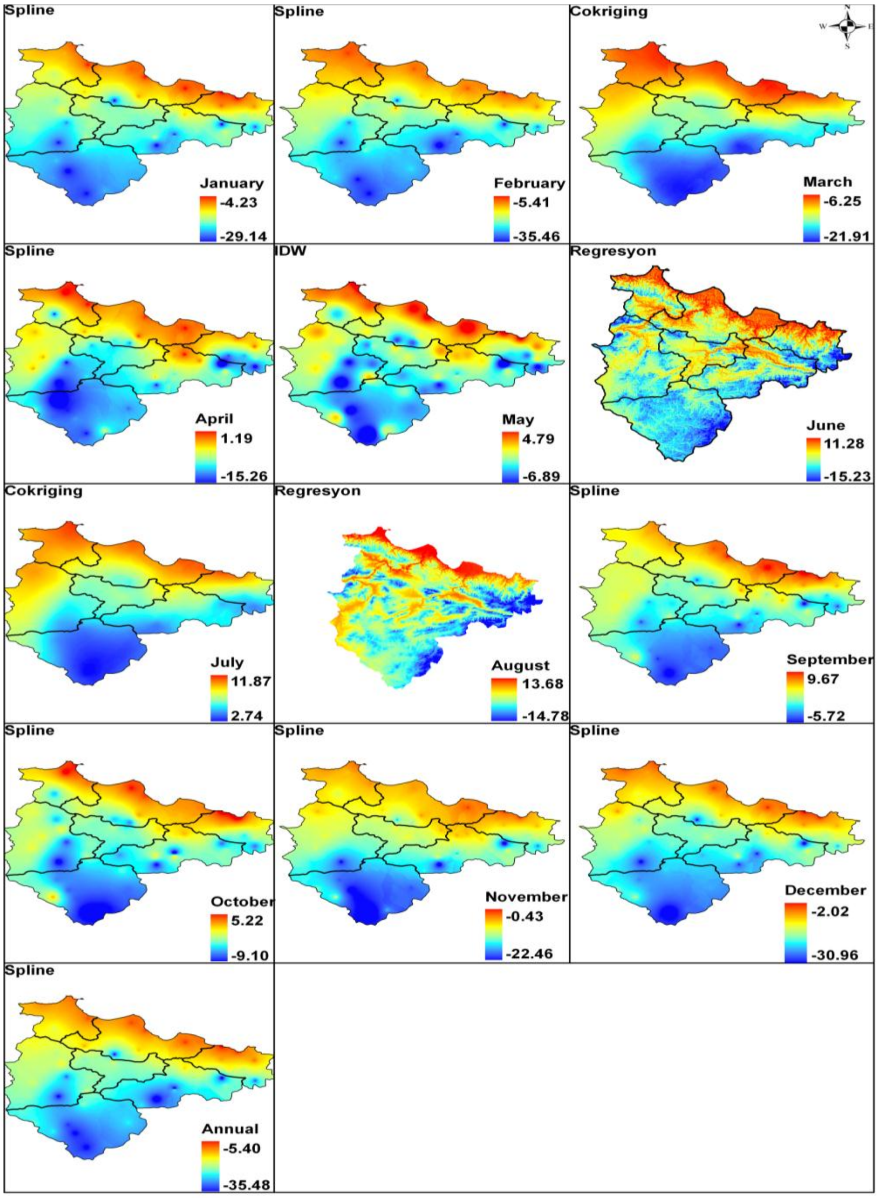

Figure 3. *Monthly minimum temperature maps produced with the most appropriate methods. All values in legends are °C.*

3.3. Maximum Temperature

The results for maximum temperatures were rather unsatisfactory compared to those for mean and minimum temperatures. Validation results were given in the Table 4. Significance level for correlation coefficients of all methods was found to be 0.01 in November, December, January and February. Significance level of MLR was found to be 0.05 in April, June, September and October, the other methods were found to be insignificant. The correlation coefficients of all the methods were found insignificant for maximum temperatures of March, May, July, August, and for annual temperature (Table 4). In general, the methods did not yield reliable results for maximum temperatures; all used methods were failed in many months. The correlation coefficients and significance levels of some months considered to be significant were also low (0.85 for January 0.93 for February, 0.86 for November and 0.91 for December 0.91).

Main reasons for such unreliable results may be due great changes in elevation of from zero to 2990 m, irregular distribution of elevations, and greater variations in maximum temperatures especially during the summer months. Higher prediction errors and lower correlation coefficients were also observed for maximum monthly temperatures of other studies. While Ninyerola et al. (2000) observed the correlation coefficients between 0.79 - 0.97 for mean and minimum temperatures, the values for maximum temperatures were between 0.60 - 0.91. Agnew and Palutikof (2000) carried out a research to produce temperature and precipitation maps in the Mediterranean waterbasin. Researchers indicated a correlation coefficient of 0.97 for winter but 0.87 for summer. It was finally concluded with regard to maximum temperatures of current study that the methods have failed and spatial distribution maps were not reliable.

4. Conclusions

Several different methods have been used to determine the spatial distribution of climate parameters and to produce climate layers. Proposed method may vary based on topographical characteristics of the research site and available number of meteorological stations within the site. A method selected as the best one for a region may not yield sufficient outcomes for another region. Reliable and sufficient data are required to select a method as the most proper one to produce climate data.

The results varied by months and methods. MLR was determined to be the most appropriate method in all months, except January, February and November; SK was determined to be the most appropriate method in January and November and CK in February. MLR yielded highly accurate results also in January, February and November. While the elevation factor was included in the models of all months, the distance from the sea was effective in the temperature change of all months except February, November and December. The sub-waterbasin elevation and slope were also included in the function of some months. It was concluded that MLR could generally be used in producing maps of monthly mean temperatures of the region. While TPS was determined as the most appropriate method for minimum temperatures of most of the months, MLR, IDW and CK methods were considered as the most appropriate methods for some months.

Table 4. *Validation results of maximum temperatures.*

	Months												
Methods[1]	January	February	March	April	May	June	July	August	September	October	November	December	Annual
IDW	0.75**	0.65*	-0.20	0.19	0.38	0.31	0.35	0.41	**0.65***	0.63*	0.68**	0.71**	0.22
TPS	0.81**	0.75**	-0.01	0.46	0.51	0.31	0.38	0.43	0.63*	**0.67****	0.68**	0.76**	0.27
SK	0.83**	0.71**	0.03	0.45	0.47	0.26	0.43	0.49	0.60*	0.65*	0.68**	0.74**	0.31
CK	0.84**	0.72**	0.08	0.46	0.46	0.25	0.51	0.36	0.63*	0.57*	0.70**	0.74**	0.27
MLR	**0.85****	**0.93****	0.45	**0.60***	0.50	**0.63***	0.33	0.45	0.52	0.45	**0.86****	**0.91****	0.25

*** and * indicate the significance level of 0.01 and 0.05, respectively*

[11]IDW (Inverse Distance Weighting), TPS (Thin-plate smoothing spline), SK (Simple Kriging), CK (Cokriging), MLR (Multiple Linear Regression)

The lowest correlation coefficient was found to be 0.80 and the highest correlation coefficient was 0.93. TPS was found as the most appropriate method in all the months except for March, May, June, July and August, MLR in June and August, CK in March and July, and IDW in May. Correlation coefficients were found to be significant at the level of 1% for all months. It was concluded that TPS may conveniently be used for production of minimum temperatures of research site.

The results obtained for maximum temperatures were rather different from the results for mean and minimum temperatures. Although no method was actually perfect for the maximum temperatures, high correlation coefficients were obtained in some months. Positive results were obtained during the winter months but all used methods failed for high temperatures especially during summer months. It is normal to have such unsatisfactory results for extreme values and irregular distributions especially in the summer months.

In current study, lack of sufficient number of observation stations and insufficient observation periods were the biggest problem with regard to climate parameters. Long-term observations and sufficient meteorological stations network is required in studies implemented over particular sites with complex topographies, similar to one considered in current study. Further research should be carried out for especially prediction of maximum temperatures of such terrains.

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