American Journal of Engineering and Applied Sciences

Original Research Paper

Mapping of Temperature Trend Slope in Iran′s Zayanderud River Basin: A Comparison of Interpolation Methods

[1]Ali Zahraei, [2]Saeid Eslamian, [3]Ali Saeidi Rizi, [2]Neda Azam, [4]Morteza Soltani, [5]Mohammad Mousavi, [6]Sona Pazdar and [7]Kaveh Ostad-Ali-Askari

[1]*Department of Irrigation and Drainage Engineering, College of Abureyhan, University of Tehran, Tehran, Iran*
[2]*Department of Water Engineering, Isfahan University of Technology, Isfahan, Iran*
[3]*Department of Civil Engineering, Shahid Bahonar University of Kerman, Kerman, Iran*
[4]*Department of Architectural Engineering, Shahinshahr Branch, Islamic Azad University, Shahinshahr, Iran*
[5]*Department of Civil Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran*
[6]*Civil Engineering Department, Aghigh University, Shahinshahr, Isfahan, Iran*
[7]*Department of Civil Engineering, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran*

Article history
Received: 19-05-2018
Revised: 05-02-2019
Accepted: 24-06-2019

Corresponding Author:
Kaveh Ostad-Ali-Askari
Department of Civil Engineering, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran
Emails: kaveh.oaa2000@gmail.com
koa.askari@khuisf.ac.ir

Abstract: The spatial distribution of daily, nightly and mean temperature trend in Iran′s Zayanderud river basin was carried out in this study by applying three approaches of interpolation including Inverse Distance Weighting (IDW), Multiple Linear Regression (MLR) and integration of these two methods (IDW+MLR). In this paper, t-test and statistical measures including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), systematic Root Mean Square Error ($RMSE_s$) and unsystematic Root Mean Square Error ($RMSE_u$) were used to evaluate the performance of approaches. This study reveals that temperature trends are inversely correlated with the altitude. All three interpolation methods overestimate in the prediction of daily and mean temperature trend and underestimate in estimating nightly temperature trend. Among three methods, IDW is the most accurate and precise in predicting daily and mean temperature trends. IDW is the most accurate and IDW+MLR is the most precise method to estimate nightly temperature trend. The MLR method for estimating nightly, mean temperature trend and the IDW method for estimating daily temperature trend have the lowest systematic error.

Keywords: Interpolation, Spatial Distribution, Temperature Trend, Ayanderud River Basin, Iran

Introduction

Climate change is one of the most interesting and concerning issues for the scientist in recent decades which is taken into account for its significant impact on natural and social systems. International Panel on Climate Change (IPCC) showed the temperature trend has been risen (0.65-1.06°C and 0.85 on average) during 1880-2012 and it is predicted that it will increase to 1.5-2°C, by the end of the 21st century. There are types of research focus on the analysis of temperature trend, including: Schnwiese and Rapp (1997); Klein Tank and Knnen (2003); Brunetti *et al.* (2000; 2004; 2006); Toreti *et al.* (2010); Wulfmeyer and Henning-Müller (2006); Rebetez and Reinhard (2008); Chaouche *et al.* (2010); Zarenistanak *et al.* (2014); Dastorani and Poormohammadi (2016). The study of the spatial distribution of temperature variables is carried out using interpolation techniques and Geographic Information Systems (GIS). There are several interpolation methods including Spline, Kriging, Inverse Distance Weighting (IDW), Regression Analysis, etc. to map spatial distribution hydrometeorological variables. Among these methods, Kriging, Inverse Distance Weighting (IDW) and multiple linear regression (MLR) are the most commonly used (Sluiter, 2009). Many studies have been conducted to compare the IDW and Kriging methods, show the IDW method is simpler, quicker and no needs too much information. These researches exhibit the same outcomes or better performance for the IDW method (Jarvis and Stuart, 2001; Stahl *et al.*, 2006; Valley *et al.*, 2005; Yunus, 2005; Weber and Englund, 1994; Gallichand and Marcotte, 1993; Dingman, 1994; Boman *et al.*, 1995; Brus *et al.*, 1996; Declercq 1996;

Science Publications

Dirks *et al*., 1998; Moyeed and Papritz, 2002). Yunus *et al*. (2015) studied the IDW interpolation method and integration of the IDW and the MLR methods to evaluate the spatial distribution of temperature in Malaysia. They showed that the integrated method offers more reliable results. The IDW and Spline methods by integration with the regression models was assessed by Kurtzman and Kadmon (1999) in Israel. In this study, the statistical analysis was used to evaluation of the performance of the methods. The results indicated that the IDW method in the winter and the Spline method in the summer make a more acceptable estimation for the temperature variables. Also, the integration of these methods with the MLP method led to increasing the accuracy in estimating extreme temperature variables. Made a comparison of the IDW, Kriging and Spline methods to prepare spatial distribution and generation of continuous data in Iraq. The results of the statistical analysis indicated that the Kriging method has better performance. Huixia *et al*. (2011) using data of 38 stations during 1960-2004 assessed the spatial interpolation by the IDW, Kriging and MLR methods in Xinjiang Uygur Autonomous Region, China. They exhibited that integration of the IDW and the MLR methods, based on statistical analysis, results in more acceptable outcomes. Anis *et al*. (2006) compared the IDW and the MLR methods to generate a spatial distribution map for temperature variables. They figured out by integrating these two methods, the precision of results in the summer and winter will increase. Bhowmik and Cabral (2011) compared the IDW, Spline and Kriging methods to interpolate temperature trend in Bangladesh by statistical measures. They showed that the IDW method is better in estimation to mean and minimum temperature trend whereas the Kriging method has a better performance for estimating maximum temperature trend. Pal and Al-Tabbaa (2010) studied the relation between temperature trend and physiographic parameters. They indicated that the changes in the temperature trend may vary in different patterns. You *et al*. (2010) investigated variations of temperature trend versus elevation in Tibetan Plateau of China. They revealed that there is a poor correlation between elevation and annual temperature trends. Vuille and Bradley (2000) studied annual temperature trend in Tropical Andes. They indicated that temperature trend is associated with elevation and reported greatest trend at low elevations.

There are lots of studies on the interpolation methods to detect spatial distribution of temperature, while there is only little research conducted on the comparison and analysis of the interpolation methods to find spatial distribution of temperature trend. In this study, three interpolation methods including IDW, MLP and integration of these two methods (IDW + MLP) are applied to map the spatial distribution of daily, mean and nightly temperature trend in Zayanderud basin. Then the performances of these methods are evaluated using statistical analysis.

Data and Methods

Zayanderud River Basin

Zayanderud river basin with an area of over 41,000 square kilometers vitalizes around 3.5 million people of central Iran. Zayandehud River originates from the western basin and flows through Isfahan megacity, finally ends Gavkhooni wetland in the eastern basin (Fig. 1). Topographic features of the basin have led to temperature variations in different parts of the basin. The annual minimum, mean and maximum temperature of the basin is 5.7, 13 and 20.5 respectively and the annual mean precipitation of the basin is 178 mm. Zayanderud river supplies urban, industrial, agricultural and environmental demands of the basin but in recent years do not able to meet all water requirements. Some studies show that increasing temperature in Zayanderud basin is one of the effective factors in an imbalance between consumptions and resources (Zareian *et al*., 2015; Gohari *et al*., 2013; Ahmadi *et al*., 2015).

Data

In this study, a data set of 37 stations in Zayanderud river basin and around it with long term maximum temperature (or daily temperature), mean temperature and minimum temperature (or nightly temperature) were studied. Monthly data during period 1951-2010 were collected from the meteorological organization and the ministry of energy and then were averaged to obtain annual data. All record lengths are more than 30 years started from 1950s, 1960s, 1970s and 1980s and ended with the year 2010. As the record length affect the validity of trends all stations with a different record length were considered (Githui, 2009). The location of the stations is shown in Fig. 2.

Sen-Slope (SS)

We evaluated the magnitude of the trend by applying the Q Sen's slope estimator developed by Sen (1968). At first the slope of N pair of data are computed by:

$$Q_k = \frac{x_j - x_i}{j - i} \; for \; k = 1, 2, ..., N \tag{1}$$

In Equation (1), x_j and x_i are the data values at times j and i ($j > i$). The median of N value of Q_k is Sen's slope which is computed as:

$$Q_{med} = \begin{cases} Q_{[N+1/2]} & if\ N\ is\ odd \\ \dfrac{Q_{\left[\frac{N}{2}\right]} + Q_{\left[N+\frac{2}{2}\right]}}{2} & if\ N\ is\ even \end{cases} \tag{2}$$

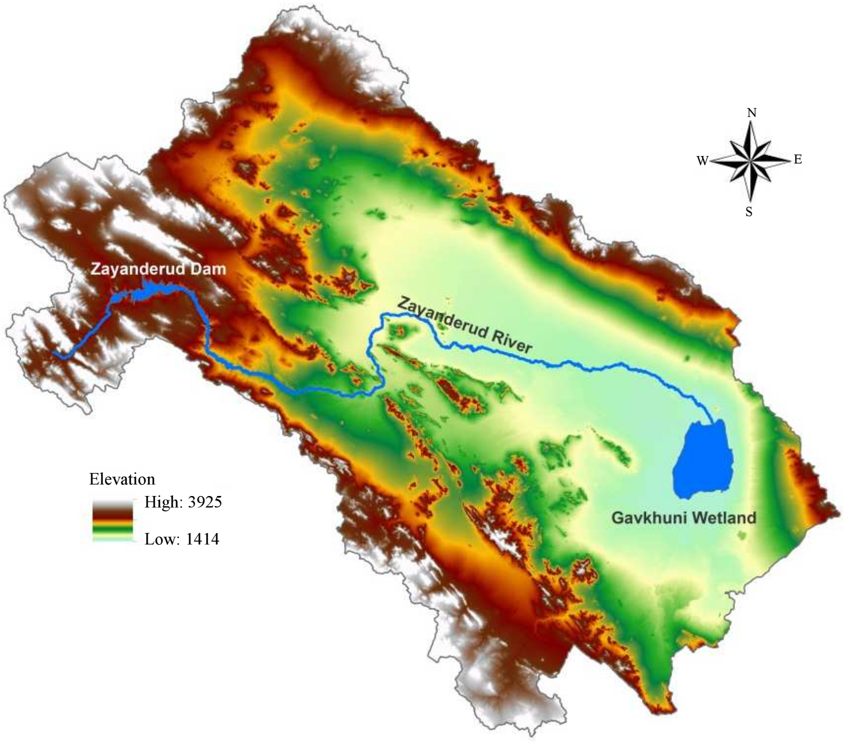

Fig. 1: Zayanderoud river basin

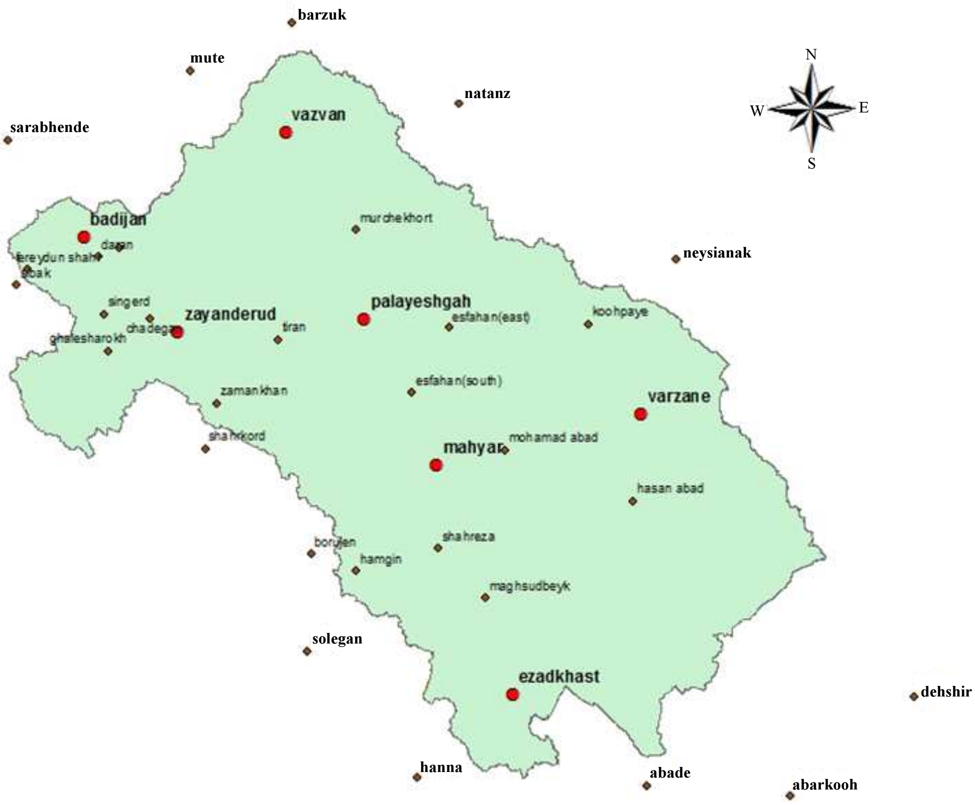

Fig. 2: The location of weather stations

In order to remove the influence of the serial correlation the pre-whitened time series before applying *Q* Sen's slope estimator is proposed (Von Storch, 1995). Serial correlation coefficient (r_1) is calculated for time series ($x_1, x_2, x_3, \ldots\ldots, x_n$) with lag-1by:

$$r_1 = \frac{\frac{1}{n-1}\sum_{i=1}^{n-1}\left(x_i - E\left(x_i\right)\right).\left(x_{i+1} - E\left(x_i\right)\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - E\left(x_i\right)\right)^2} \quad (3)$$

$$E\left(x_i\right) = \frac{1}{n}\sum_{i=1}^{n}\left(x_i\right) \quad (4)$$

where, n is the number of data and $E(x_i)$ is the mean of sample data. If calculated r_1 is not significant at the 5% level, *Q* Sen's Slop estimator is done for the original data, otherwise, it will be done on pre-whitened time series (x_2-r_1x_3, x_3-r_1x_2……, x_n-r_1x_{n-1}) (Islam, 2015).

Inverse Distance Weighting (IDW)

IDW is an interpolation method based on the assumption that nearby points have more influences on the predicted measure than distant points. The procedure is simple to agenda, "data driven" and quite automated. It prepares a pragmatic assess of doubt for each forecasted location and could be readily expanded to 3-dimentional cases. Each point gets inverse weight measure based on to their distance to the point measure of which will be predicted. The estimate at x_0 point is computed by Equation (6) (Bayazit *et al.*, 2016):

$$w\left(d_i\right) = \frac{\frac{1}{d_i^p\left(x_i\right)}}{\sum_{i=1}^{n}\frac{1}{d_i^p\left(x_i\right)}} \quad (5)$$

$$Z^*\left(x_0\right) = \left[\sum_{i=1}^{n} w\left(d_i\right) Z\left(x_i\right)\right] / \left[\sum_{i=1}^{n} w\left(d_i\right)\right] \quad (6)$$

$Z^*(x_0)$ shows predicted measure of x_0 point and $Z(x_i)$ indicates the measure of sample point at x_i point. $w(d_i)$ is the weighting function and d_i is the distance from x_i to x_0. p is the power factor and n is the number of sample points. The user has control over the mathematical form of the weighting function by the selected size of the neighborhood (expressed as a number of points) and power factor. In this study, considering the scatter of station in the basin, we test 3 to 15 nearest stations and for each size of neighborhood, the power factor (p) will be optimized in Arc GIS automatically. The number of stations and power factor getting the lowest RMSE is chosen.

Multiple Linear Regression (MLR)

MLR is another method of interpolation analyzed in this study. We used backward elimination for variable selection to apply multiple linear regression. In this approach, firstly we computed the regression equation including all variables and then at each step we eliminated a variable based on partial P-value. If a variable was not significant then we dropped it from the equation and recalculated the regression using the rest of variables. This process continued to get an equation with significant variables (Anis *et al.*, 2006).

Integrated Method (IDW + MLR)

The multiple linear regression model was integrated with IDW interpolation technique by interpolating residual of *S-S′*, where S was observed *Q* Sen's slope and *S′* was estimated *Q* Sen's slope from the multiple linear regression model. At first *S-S′* values were computed in each station and then by interpolation (IDW method), *S-S′* layer was created in ArcGIS. To generate map of the integrated method, *S-S′* raster layer was added to *S′* raster layer (Jarvis and Stuart, 2001; Kurtzman and Kadmon, 1999; Yunus *et al.*, 2015).

Performance Measures

The difference between observed and estimated values is described by Root Mean Square Error (RMSE) or Mean Absolute Error (MAE) according to Equation (7) and (8). These two statistics are used to assessment of model accuracy (the accuracy is defined as the degree to which model-estimated values approach the magnitudes of their observed counterparts). MAE in comparison with RMSE has less sensitivity to extremes variables. In ideal condition and if a model be perfect the values of RMSE and MAE will be zero (Fox, 1981; Willmott *et al.*, 1985):

$$RMSE = \left[N^{-1}\sum_{i=1}^{N}\left(P_i - O_i\right)^2\right]^{0.5} \quad (7)$$

$$MAE = N^{-1}\sum_{i=1}^{N}\left| P_i - O_i \right| \quad (8)$$

In Equations (7) and (8) N is the number of data, P_i is estimated data and O_i is observed data. Linear bias produced by model can be described by systematic error and model precision is evaluated by unsystematic or random error. By random error we evaluate ability of models to estimate same values for the same observations (Willmott *et al.*, 1985). Willmott (1981) suggested Equations (10) and (11) to quantify systematic ($RMSE_s$) and unsystematic error ($RMSE_u$):

$$RMSE_s = N^{-1}\sum_{i=1}^{N}\left(P_i^{\wedge} - O_i\right)^2 \quad (9)$$

$$RMSE_u = N^{-1}\sum_{i=1}^{N}\left(P_i - P_i^{\wedge}\right)^2 \quad (10)$$

$$RMSE = \sqrt{RMSE_s^2 + RMSE_u^2} \quad (11)$$

A model can be accurate but not precise, precise but not accurate, neither or both.

In-Depth Statistical Evaluation Method

In this study, we compared the mean of estimated and observed values using paired sample t-test to figure out if results of two methods were significantly different. In this test, Method1, Method2 and Method3 were used to show IDW, MLR and MLR+IDW methods. For instance, if the difference between observed and estimated values in Method1 was smaller than Method2, $X_2 = E$ (Method2)-O and X_1 = E (Method1)-O were defined, where O is the observed value and E (Method1), E (Method2) are the estimated values from Method 1 and 2. The hypothesis of H_o: $\mu_{x1}<\mu_{x2}$ would be tested with the confidence level of 95% and it would be acceptable if P-value was smaller than 0.05 (You *et al*., 2008).

Results and Discussion

Trend slope of nightly, daily and mean temperature (S_{Tmin}, S_{Tmax}, S_{Tmean}) were calculated by Q Sen's slope estimator for all stations (Table 1). Then IDW, MLR and the integrated method (IDW + MLR) were applied using 70% of stations to generate spatial distribution map in Zayanderud basin. For each method cross validation analysis was carried out using the rest of 30% data. The general assessment of methods was performed by t-test and the detailed analysis was done by performance measures. We selected 7 stations from different part of the basin (mountainous and flat areas) to evaluate results of the models as follows: Vazvan, Varzane, Zayanderud Palayeshgah, Badijan, Mahyar, Ezadkhast shown in Fig. 2 with bolded names and red points.

IDW

Optimal power factor for each number of neighbors is determined in Arc-GIS. We tested several neighbors (3-15 stations) and selected power factor and size of the neighborhood based on the lowest root mean square error as follows: (1.07, 14) for S_{Tmax}, (1.12, 10) for S_{Tmean} and (2.55, 4) for S_{Tmin}. These outcomes were used to generate the spatial distribution map of trend. The generated map by the IDW method is shown in Fig. 3. The generated maps in this method show smooth variation of trends without a specific pattern but the urban heat island effect (significant warming due to human activities) is very obvious in these maps. Due to "bull's-eye" effect in the IDW method, the heat island effect has shown in the form of circular region surrounding urban areas.

MLR

Physiographic parameters including x coordinate (latitude), y coordinate (longitude) and h (altitude) were used as the predictors of trend slope in the regression model. The regression equations for S_{Tmax}, S_{Tmean} and S_{Tmin} were calculated using 70% of stations and tested in 95% confidence level (Table 2). The results show the inverse relationship between temperature trend slope and elevation for nightly, daily and mean temperature. By these Regression equations the spatial distribution map of trend were generated and presented in Fig. 4. The produced maps in this method have topographic patterns and can exhibit natural variation of trends in different landforms (valleys or hills).

Table 1: The magnitude of trends in stations (C°/year)

Station	S_{Tmax}	S_{Tmean}	S_{Tmin}
varzane	0.008	0.006	0.032
hasan abad	0.007	0.022	0.033
abarkooh	0.001	0.011	0.014
esfahan(east)	0.006	0.015	0.013
esfahan(south)	0.011	0.018	0.013
mohamad abad	0.012	0.015	0.010
natanz	0.009	0.021	0.027
mahyar	0.008	0.016	0.021
murchekhort	0.011	0.017	0.019
palayeshgah	0.000	0.016	0.019
tiran	0.020	0.027	0.026
dehshir	-0.003	0.007	0.010
zamankhan	-0.005	0.006	0.018
shahreza	-0.004	0.010	0.012
neysianak	0.010	0.012	0.017
koohpaye	0.013	0.013	0.005
mute	0.012	0.015	0.014
maghsudbeyk	0.003	0.015	0.018
vazvan	-0.005	-0.001	0.005
abade	0.000	0.008	0.011
sarabhende	0.004	0.019	0.025
barzuk	0.008	0.017	0.017
shahrkord	-0.007	-0.009	-0.008
ghalesharokh	-0.014	-0.009	-0.003
zayanderud	-0.005	0.008	0.009
singerd	-0.003	-0.001	0.001
chadegan	0.002	0.013	0.012
solegan	-0.001	0.000	0.002
ezadkhast	0.007	0.015	0.022
borujen	0.002	0.006	0.007
hamgin	-0.007	0.002	0.010
hanna	-0.006	0.025	0.044
daran	-0.004	0.010	0.014
damane	0.014	0.006	0.002
badijan	0.006	0.010	0.016
sibak	-0.005	0.003	0.007
fereydun shahr	-0.006	0.012	0.019

Table 2: Multiple linear regression coefficients of trend slope with physiographic parameters

	S_{Tmax}			S_{Tmean}			S_{Tmin}		
parameter	Coefficient	P-value	R	Coefficient	P-value	R	Coefficient	P-value	R
Intercept	-	-	0.61	-	-	0.89	-	-	0.89
h	-1.5E-05	0.00163		-1.5E-05	0.00128		-1.3E-05	0.01127	
x	-	-		-	-		-	-	
y	9.1E-09	0.00079		1.1E-08	0.00004		1.1E-08	0.00037	

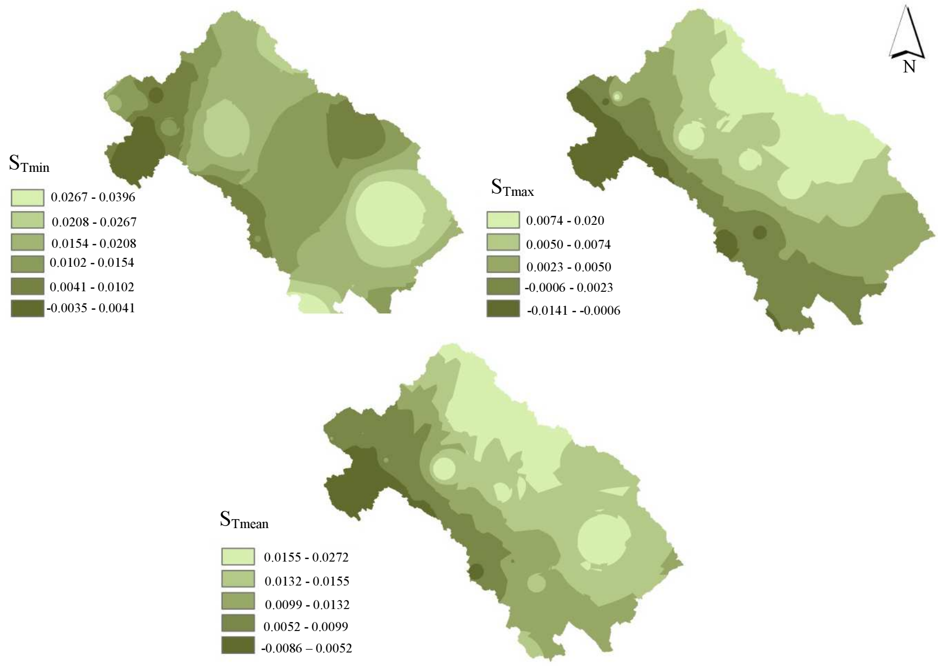

Fig. 3: Spatial distribution of temperature trend in IDW method

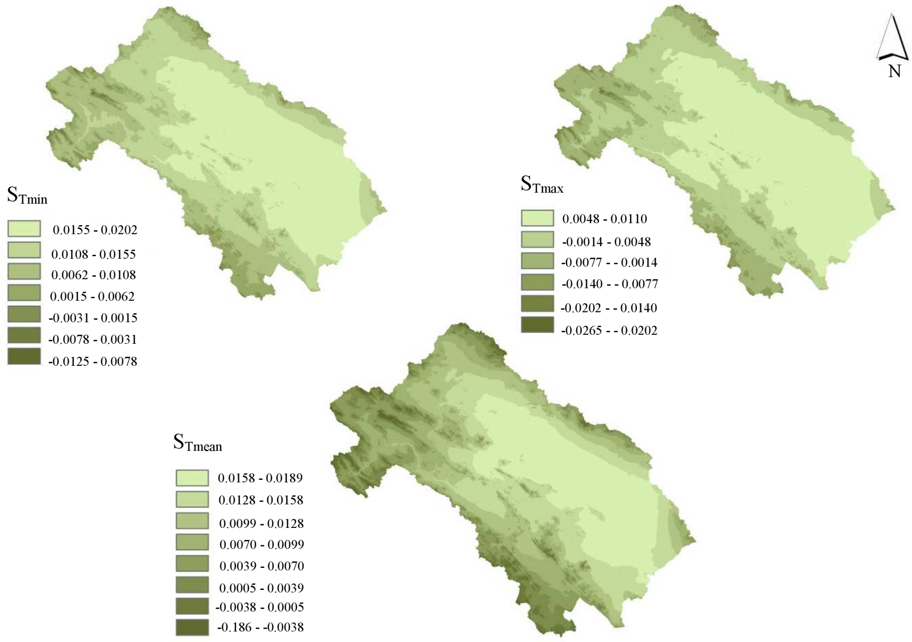

Fig. 4: Spatial distribution of temperature trend in MLR method

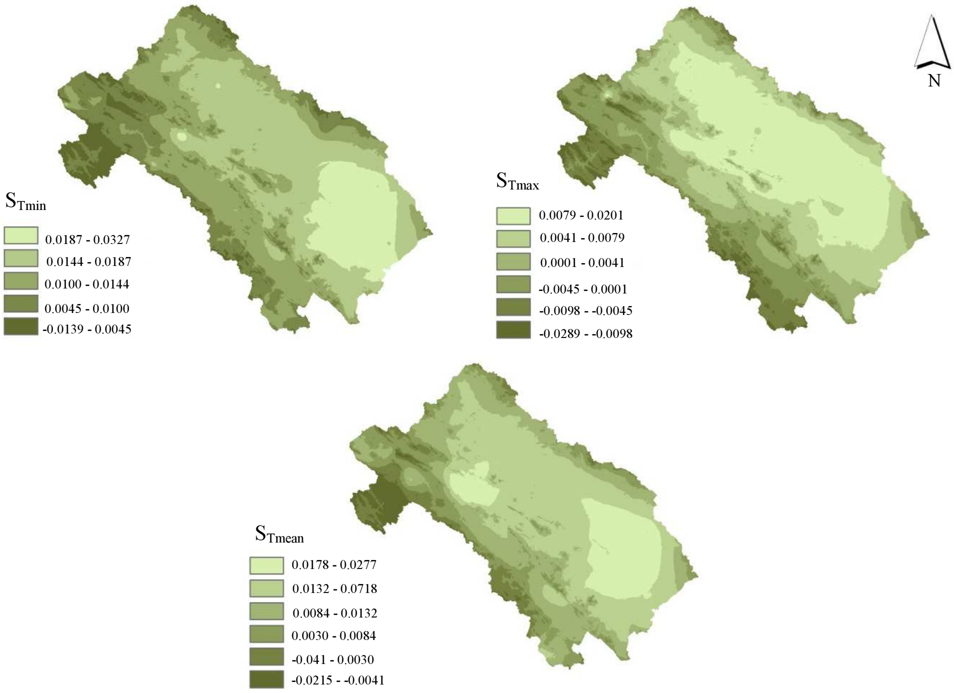

Fig. 5: Spatial distribution of temperature trend in IDW+MLR method

MLR + IDW

Using the calculated equations in the MLR method we estimated trend slope in each station (S') and then for interpolating residual of S-S' in the IDW method, the optimized power factors and the number of neighbors were computed in ArcGIS as it mentioned in 3.1.1 section. Power factor and number of neighbors for S_{Tmax}, S_{Tmean} and S_{Tmin} are (1, 10), (2.5, 15) and (1, 14) respectively. The generated map in the integrated method is shown in Fig. 5. Spatial distribution of trends in this method, in addition to have topographic patterns can show the urban heat island effect in some part of the basin particularly for S_{Tmin} and S_{Tmean}.

Comparison of Observed to Estimated

Figure 6 shows observed and estimated measures for all three methods in 7 selected stations (30% of data). All methods overestimated maximum temperature trend. The magnitude of overestimation for IDW is 0.0014°C/year, for MLR 0.0080°C/year and for (IDW + MLR) 0.0019°C/year. Also there is an overestimation in all methods to compute the mean temperature trend by 0.0032°C/year, 0.0016°C/year and 0.0023°C/year for IDW, MLR, IDW+MLR respectively. But in prediction of minimum temperature trend, there is an underestimation in all three methods by 0.0019°C/year, 0.0040°C/year, 0.0041°C/year for IDW, MLR, IDW+MLR respectively.

Cross Validation Analysis

Performance of the Methods Using T-Test

The average difference between observed and estimated S_{Tmax} in applying IDW, MLR and IDW+MLR methods (X_1, X_2, X_3) are 0.0056°C/year, 0.0058°C/year, 0.0069°C/year, respectively. The maximum and minimum difference is seen in the results of the MLR + IDW and IDW method respectively. The average of X_1, X_2 and X_3 for S_{Tmean} are 0.0049°C/year, 0.0058°C/year and 0.0057°C/year, respectively which the maximum and minimum are observed in the MLR and the IDW method. The average of X_1, X_2 and X_3 for S_{Tmin} are 0.0059°C/year, 0.0071°C/year and 0.0069°C/year, respectively and the maximum, minimum occur in the MLR and IDW methods respectively. The superiority of each method to another was tested by the paired sample t-test with the confidence level of 0.95 and the results are shown in Table 3. The p-values of all tests for daily, nightly and mean temperature were greater than 0.05 and none of the methods have no significant advantage over the other.

Performance of the Methods using MAE, RMSE, $RMSE_s$, $RMSE_u$

S_{Tmax}

The performance measures were calculated for the estimation of maximum temperature trend (Table 4). The results show that the values of MAE and RMSE for the

IDW and MLR methods approximately are the same but in general, these values for the IDW+MLR are higher than two other methods by 0.0011 to 0.0016°C/year; hence the IDW and the MLR methods estimate S_{Tmax} more accurate than the IDW + MLR method. The systematic error of the IDW method is 78% of the mean-square-error which is higher than the MLR and IDW + MLR methods (53%, 53%). Non-systematic error for the IDW, the MLR and the IDW+MLR methods are 22%, 47% and 47% of the mean-square-error respectively, show the IDW method is more precise than the other methods. The other two methods have the same precision to estimate the trend slope. Comparison of errors in each method exhibits that there is more portion of systematic error than a random error in the IDW, but in the other two methods, the portion of random and systematic errors is the same.

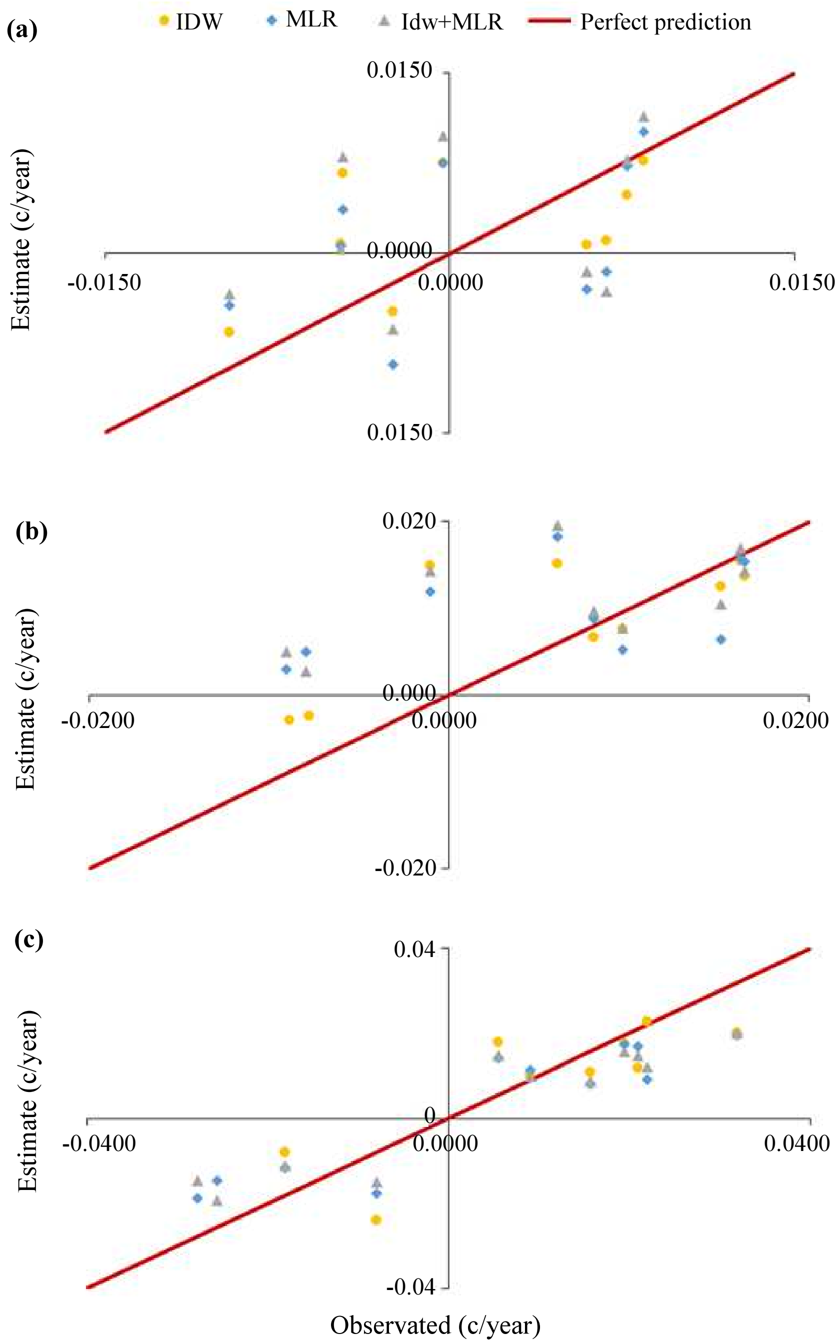

Fig. 6: Comparison of observed to estimate for IDW, MLR and IDW+MLR methods for (a) S_{Tmax}, (b) S_{Tmean}, (c)S_{Tmin}

Table 3: The results of t-test

Variable	Hypothesis	P-value	Result
ST_{max}	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_2 \rvert}$	0.81	Reject
	H0: $\mu_{\lvert x_2 \rvert} < \mu_{\lvert x_3 \rvert}$	0.20	Reject
	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_3 \rvert}$	0.18	Reject
ST_{mean}	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_2 \rvert}$	0.49	Reject
	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_3 \rvert}$	0.31	Reject
	H0: $\mu_{\lvert x_3 \rvert} < \mu_{\lvert x_2 \rvert}$	0.93	Reject
ST_{min}	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_2 \rvert}$	0.55	Reject
	H0: $\mu_{\lvert x_1 \rvert} < \mu_{\lvert x_3 \rvert}$	0.49	Reject
	H0: $\mu_{\lvert x_3 \rvert} < \mu_{\lvert x_2 \rvert}$	0.82	Reject

Table 4: Quantitative measures of model performance (°C/year)

Variable	Type of error	IDW	MLR	MLR + IDW
S_{Tmax}	*MAE*	0.0056	0.0058	0.0069
	RMSE	0.0064	0.0067	0.0080
	$RMSE_s$	0.0057	0.0048	0.0059
	$RMSE_u$	0.0030	0.0046	0.0055
S_{Tmean}	*MAE*	0.0049	0.0058	0.0057
	RMSE	0.0072	0.0077	0.0080
	$RMSE_s$	0.0063	0.0062	0.0070
	$RMSE_u$	0.0034	0.0046	0.0039
S_{Tmin}	*MAE*	0.0059	0.0069	0.0071
	RMSE	0.0076	0.0078	0.0082
	$RMSE_s$	0.0064	0.0072	0.0074
	$RMSE_u$	0.0041	0.0029	0.0036

S_{Tmean}

The performance measures in Table 4 show the values of MAE, RMSE in the IDW method are lower than other methods by 0.0006 to 0.0009°C/year. In the other words the IDW method estimates S_{Tmean} more accurate by 0.0006 to 0.0009°C/year in comparison with other methods. The systematic errors of the IDW, MLR and MLR+IDW methods are 78%, 64% and 77% of mean-square-errors, respectively. The random errors of IDW, MLR and MLR+IDW are 22%, 36% and 23% of mean-square-errors, respectively. Therefore, the estimation of S_{Tmean} by the IDW and MLR+IDW methods are more precise than MLR. Review of the errors in all three methods show the systematic error is more than random error.

S_{Tmin}

The values of MAE and RMSE to the estimation of S_{Tmin} (Table 4) indicate the IDW method with the lower error, estimates S_{Tmin} more accurate by 0.0002 to 0.0012°C/year than two other methods. The systematic errors of IDW, MLR and MLR+IDW are 71%, 81% and 86% of mean-square-error, respectively. The computed random errors for IDW, MLR, MLR+IDW are 29%, 19%, 14% of mean-square-error respectively, shows the most precise methods is MLR+IDW. In all three methods, comparison of errors indicates the portion of systematic error is more than random error.

Conclusion

This study aims to the investigation of interpolation methods to map the daily, nightly and mean temperature trend in Zayanderud river basin. 37 meteorological stations were studied and using Q Sen's slope estimator, the magnitude of trend was determined in each station. For mapping, the trends, three interpolation methods including Inverse Distance Weighting (IDW), Multiple Linear Regression (MLR) and IDW + MLR (integration of IDW and MLR) were applied and then the estimation of methods were analyzed by t-test and performance measures. The outcomes of the MLR method showed that the nightly, daily and mean temperature trends are associated with the elevation and latitude significantly. All three temperatures have a direct relation with latitude and inverse relation with elevation (similar to the relation between temperature and elevation) and the correlations for mean and nightly were stronger than daily temperature trend. The generated maps by the IDW method can exhibit human-induced changes in temperature better than other methods whereas the maps of MLR and integrated methods can nicely indicate natural changes of trend. The results indicated all three interpolation methods overestimate S_{Tmax} and S_{Tmean} and underestimate S_{Tmin}. The general comparison between observed and estimated values by t-test exhibited no significant difference among methods whereas the detailed comparison by performance measures showed the estimates of the IDW method are the most accurate and precise for S_{Tmax} and S_{Tmean}. Regarding the estimation of S_{Tmin}, findings indicated the IDW method is the most accurate method and integrated method is the most precise method. The results showed that in all three methods, systematic error is higher than non-systematic error. The systematic errors for estimation of S_{Tmax} and S_{Tmean} by the MLR method are lower than other methods whereas this error in the IDW method is the lowest for the estimate of S_{Tmin}. The findings of this study can be helpful to obtain a more reliable prediction of temperature trend in different zones of the Zayanderud river basin. Regard the Table 3 the least error is about RMSEu (S_{tmin}, MLR) equals 0.0029 and the highest error is about RMSE (S_{tmean}, MLR + IDW) equlas 0.0082. but the interpolation three of method is closely the answer of the error of the model performance.

Acknowledgment

This research was supported by the Isfahan University of the Technology. We thank our all authors who provided insight and expertise that greatly assisted the research.

Author's Contributions

All authors contributed to design the study, write and revise the manuscript.

Ethics

The present Study and ethical aspect were approved by the Isfahan University of the Technology. The present study was approved by the Isfahan University of Technology.

References

Ahmadi, A., A. Khoramian and H.R. Safavi, 2015. Assessment of climate change impacts on snow-runoff processes a case study: Zayanderoud river Basin (In Persian). Iran-Water Resources Res., 11: 70-82.

Anis, R., F. Saeed and R. Aslam, 2006. Comparison of different interpolation methods for temperature mapping in Pakistan, Global Change Impact Studies Centere, Jinnah Avenue, Islamabad, Pakistan, The 2nd International Conf. on Water Resources and Arid Environment.

Bayazit, Y., R. Bakiş and C. Koç, 2016. Mapping distribution of precipitation, temperature and evaporation in seydisuyu basin with the help of distance related estimation methods. J. Geographic Inform. Syst., 8: 224-237. DOI: 10.4236/jgis.2016.82020

Bhowmik, A.K. and P. Cabral, 2011. Statistical evaluation of spatial interpolation methods for small-sampled region: A case study of temperature change phenomenon in Bangladesh. Proceedings of the International Conference of Computational Science and Applications, Jun. 20-23, Santander, Spain, pp: 44-59.

Boman, G., F.J. Molz and O. Guven, 1995. An evaluation of interpolation methodologies for generating three-dimensional hydraulic property distributions from measured data. Ground Water, 33: 247-258. DOI: 10.1111/j.1745-6584.1995.tb00279.x

Brunetti, M., L. Buffoni, M. Maugeri and T. Nanni, 2000. Trends of minimum and maximum daily temperatures in Italy from 1865 to 1996. Theoretical Applied Climatol., 66: 49-60. DOI: 10.1007/s007040070032

Brunetti, M., L. Buffoni, F. Mangianti, M. Maugeri and T. Nanni, 2004. Temperature, precipitation and extreme events during the last century in Italy. Global Planetary Change, 40: 141-149. DOI: 10.1016/S0921-8181(03)00104-8

Brunetti, M., M. Maugeri, F. Monti and T. Nannia, 2006. Temperature and precipitation variability in Italy in the last two centuries from homogenised instrumental time series. Int. J. Climatol., 26: 345-381. DOI: 10.1002/joc.1251

Brus, D.J., J.J. de Gruijter, B.A. Marsman, R. Visschers and A.K. Bregt *et al*., 1996. The performance of spatial interpolation methods and choropleth maps to estimate properties at points: A soil survey case study. Environmetrics, 7: 1-16. DOI: 10.1002/(SICI)1099-095X(199601)7:1<1::AID-ENV157>3.0.CO;2-Y

Chaouche, K., L. Neppel, C. Dieulin, N. Pujol and B. Ladouche *et al*., 2010. Analyses of precipitation, temperature and evapotranspiration in a French Mediterranean region in the context of climate change. Comptes Rendus Geosci., 342: 234-243. DOI: 10.1016/j.crte.2010.02.001

Dastorani, M.T. and S. Poormohammadi, 2016. Mapping of climatic parameters under climate change impacts in Iran. Chem. Ecol. Hydrol. Sci. J. DOI: 10.1080/02626667.2015.1131898

Declercq, F.A.N., 1996. Interpolation methods for scattered sample data: Accuracy, spatial patterns, processing time. Cartography Geographic Inform. Syst., 23: 128-144. DOI: 10.1559/152304096782438882

Dingman, S.L., 1994. Physical Hydrology. 1st Edn., Macmillan College Publishing Company.

Dirks, K.N., J.E. Hay, C.D. Stow and D. Harris, 1998. High-resolution studies of rainfall on Norfolk Island part II: Interpolation of rainfall data. J. Hydrol., 208: 187-193. DOI: 10.1016/S0022-1694(98)00155-3

Fox, D.G., 1981. Judging air quality model performance: A summary of the AMS workshop on dispersion model performance. Bull. Am. Meteorol. Soc., 62: 559-609. DOI: 10.1175/1520-0477(1981)062<0599:JAQMP>2.0.CO;2

Gallichand, J. and D. Marcotte, 1993. Mapping clay content for subsurface drainage in the Nile Delta. Geoderma, 58: 165-179. DOI: 10.1016/0016-7061(93)90040-R

Githui, F.W., 2009. Assessing the impacts of environmental change on the hydrology of the Nzoia catchment, in the Lake Victoria Basin. PhD Thesis, Vrije University Brussel.

Gohari, A., S. Eslamian, J. Abedi-Koupai, A. Massah Bavani and D. Wang *et al*., 2013. Climate change impacts on crop production in Iran's Zayandeh-Rud River Basin. Sci. Total Environ., 442: 405-419. DOI: 10.1016/j.scitotenv.2012.10.029

Huixia, C., C. Weiming, Z. Chenghu, C. Xi and M. Xiaoyi *et al*., 2011. Analysis and comparison of spatial interpolation methods for temperature data in Xinjiang Uygur Autonomous Region, China. Natural Sci., 3: 999-1010. DOI: 10.4236/ns.2011.312125

Islam, A.W., 2015. Rainy/non-rainy day pattern analysis for North Carolina. Am. J. Climate Change, 4: 1-8. DOI: 10.4236/ajcc.2015.41001

Jarvis, C.H. and N. Stuart, 2001. A comparison among strategies for interpolating maximum and minimum daily air temperatures, Part II: The interaction between number of guiding variables and the type of interpolation method. J. Applied Meteorol., 40: 1075-1084. DOI: 10.1175/1520-0450(2001)040<1075:ACASFI>2.0.CO;2

Klein Tank, A.M.G. and G.P. Konnen, 2003. Trends in indices of daily temperature and precipitation extremes in Europe 1946–99. J. Climate, 22: 3665-3680. DOI: 10.1175/1520-0442(2003)016<3665:TIIODT>2.0.CO;2

Kurtzman, D. and R. Kadmon, 1999. Mapping of temperature variables in Israel: A comparison of different interpolation methods. Climate Res., 13: 11-21. DOI: 10.3354/cr013033

Moyeed, R.A. and A. Papritz, 2002. An empirical comparison of kriging methods for nonlinear spatial point prediction. Math. Geol., 34: 365-386. DOI: 10.1023/A:1015085810154

Pal, I. and A. Al-Tabbaa, 2010. Long-term changes and variability of monthly extreme temperatures in India. Theor Applied Climatol., 100: 45-56. DOI: 10.1007/s00704-009-0167-0

Rebetez, M. and M. Reinhard, 2008. Monthly air temperature trends in Switzerland 1901-2000 and 1975-2004. Theor. Applied Climatol., 91: 27-34. DOI: 10.1007/s00704-007-0296-2

Sen, P.K., 1968. Estimates of regression coefficient based on Kendall's tau. J. Am. Stat. Assoc., 63: 1379-1389. DOI: 10.1080/01621459.1968.10480934

Schnwiese, C.D. and J. Rapp, 1997. Climate Trend Atlas of Europe based on Observations 1891-1990. Kulver Academic Publishers, Dordrecht. pp: 235.

Sluiter, R., 2009. Interpolation methods for climate data -literature review. KNMI, R&D Information and Observation Technology De Bilt, Netherlands.

Stahl, K., R.D. Moore, J.A. Floyer, M.G. Asplin and I.G. McKendry, 2006. Comparison of approaches for spatial interpolation of daily air temperature in a large region with complex topography and highly variable station density. Agric. Forest Meteorol., 139: 224-236. DOI: 10.1016/j.agrformet.2006.07.004

Toreti, A., E. Xoplaki and D. Maraun, 2010. Characterisation of extreme winter precipitation in Mediterranean coastal sites and associated anomalous atmospheric circulation patterns. Nat. Hazards Earth Syst. Sci., 10; 1037-1050. DOI: 10.5194/nhess-10-1037-2010.

Yunus, F., 2005. Assessment of spatial interpolation techniques of temperature elements in peninsular Malaysia. MSc Thesis, University Putra Malaysia.

Yunus, F., N.K. Chang, F.J. Fakaruddin, M.K. Mat Adam and J. Jaafar *et al*., 2015. Modelling of surface air temperature element in Malaysia. Dev. Earth Sci. DOI: 10.14355/des.2015.03.002

You, J., K.G. Hubbard and S. Goddard, 2008. Comparison of methods for spatially estimating station temperatures in a quality control system. Int. J. Climatol., 28: 777-787. DOI: 10.1002/joc.1571

You, O., S. Shichang Kang, N. Pepin, W.A. Flügel and Y. Yan *et al*., 2010. Relationship between temperature trend magnitude, elevation and mean temperature in the Tibetan Plateau from homogenized surface stations and reanalysis data. Global Planetary Change, 71: 124-133. DOI: 10.1016/j.gloplacha.2010.01.020

Valley, R.D., M.T. Drake and C.S. Anderson, 2005. Evaluation of alternative interpolation techniques for the mapping of remotely-sensed submersed vegetation abundance. Aquatic Botani, 81: 13-25. DOI: 10.1016/j.aquabot.2004.09.002

Vuille, M. and R.S. Bradley, 2000. Mean annual temperature trends and their vertical structure in the tropical Andes. Geophys. Res. Lett., 27: 3885-3888. DOI: 10.1029/2000GL011871

Von Storch, H., 1995. Misuses of Statistical Analysis in Climate Research. In: Analysis of Climate Variability: Applications of Statistical Techniques, Storch, H.V. and A. Navarra (Eds.), Springer, Berlin, pp: 11-26.

Weber, D.D. and E.J. Englund, 1994. Evaluation and comparison of spatial interpolators. Math. Geol., 24: 381-391. DOI: 10.1007/BF00891270

Willmott, C.J., 1981. On the valdation of models. Phys. Geogr., 2: 184-194. DOI: 10.1080/02723646.1981.10642213

Willmott, C.J., S.G. Ackleson, R.E. Davis, J.J. Feddema and K.M. Klink *et al*., 1985. Statistics for the evaluation and comparison of models. J. Geophys. Res., 90: 8995-9005. DOI: 10.1029/JC090iC05p08995

Wulfmeyer, V. and I. Henning-Müller, 2006. The climate station of the University of Hohenheim: Analyses of air temperature and precipitation time series since 1878. Int. J. Climatol., 26: 113-138. DOI: 10.1002/joc.1240

Zarenistanak, M., A.G. Dhorde and R.H. Kripalani, 2014. Temperature analysis over southwest Iran: Trends and projections. Theor. Applied Climatol., 116: 103-117. DOI: 10.1007/s00704-013-0913-1

Zareian, M.J., S. Eslamian, H.R. Safavi and A. Eslamian, 2015. Effect of climate change on reference evapotranspiration based on weighting methods. Proceedings of the 4th Climate Change Technology Conference, May 25-27, Montreal, Canada.