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Comparison of Different Interpolation Methods for Temperature Mapping in Pakistan

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Abstract

Interpolation of climate variables from point data to large areas is important in variety of disciplines. Each of the 50 meteorological stations in Pakistan area represents an average area of approximately16,000 square kilometer. Therefore it is important to minimize the extent of interpolation errors by using a suitable interpolation method. In this study we compared the performance of 2 local interpolation methods, Inverse Distance Weighting (IDW) and Inverse Distance Weighting with Elevation Correction (IDWEC), with the performance of multiple regression models. These interpolation methods are applied to 4 temperature variables: averaged monthly minimum temperature of the coldest month (January), averaged monthly maximum temperature of the warmest month (June), averaged monthly mean temperature of summer (April-September) and averaged monthly mean temperature of winter (October-March). The multiple regression models are based on geographic longitude, latitude and elevation and included terms of first and second order. Three methods of variable selection (Backward Elimination, Stepwise, and Forced Entry) are used to construct 3 regression models for each temperature variable. Accuracy is assessed by a one-left-out cross validation test. Seasonal temperature variables proved more predictable than extreme temperature variables. For the 2 summer variables and 2 winter variables, IDWEC and Backward Elimination method are showing best statistics. However, Backward Elimination method is considered to be the preferred method over IDWEC. Combining multiple regression and local interpolation methods improved prediction accuracy for summer variables but not for winter variables. Where the data supported strong short-range climatic factors (such as the westerly disturbances and Monsoon), local methods are more effective than regression models.
Keywords: Climate variables, Interpolation methods, Inverse Distance Weighting, Regression models, Pakistan.

Introduction

Climate data exist as measurements at discrete points normally called as meteorological stations and many different methods have evolved to generate regional maps from point data. Point data may be interpolated to a regular grid using a variety of methods for determining weights for measured sites, generally as a function of distance or pattern of spatial variance. Interpolated surfaces of climate variables are useful in many different areas of research. Amongst these are hydrology (Schreider et al. 1997), climate (Kurtzman & Kadmon 1999), ecology (Box et al. 1993), epidemiology (Lindsay et al. 1998) and physiology (Goodale et al. 1998). Interpolation methods include Thiessen polygons (Thiessen. 1911), Inverse Distance interpolation (Willmott & Matsuura 1995, Dodson & Marks 1997) and kriging (Holdaway 1996). It is also common to these studies that they use variables such as elevations, latitude and longitude as predictors of climatic variables. Some authors use methods where trends lie within the interpolator, for example the various versions of Universal Kriging (Hudson & Wackernagel 1994) where a 2-dimensional trend is built in (Hulme et al. 1995), whilst others detrend the data and interpolate the residuals (Kurtzman and Kadmon 1999).

It is believed that Global Warming is the biggest threat for the world in 21st century and International Panel on Climate Change (IPCC) has protected an increase of 1.4-5.8ºC in the average global temperature by the end of this century. This issue is of particular concern for Pakistan since its economy is heavily dependent upon Agriculture, which in turn depends upon the melt water coming from the glaciers and snowmelt of Hidukush-karakoram-Himalayan (HKH) region. Under the future scenario of Global Warming, these glaciers are under threat and different reports suggested that these glaciers are going to disappear by 2050 (Rees & Collins 2004). Now authorities are taking interest in the effects of this warming through dynamic downscaling of Global Circulation Models (GCMs) data through Regional Climate Models (RCMs) so that appropriate adaptation measures could be taken in order to cope with the adverse effects of this changing climate.

In order to calibrate and validate RCMs, it is necessary to generate the gridded data sets of different variables including temperature from point data. UK met office has generated monthly gridded data sets for different climate variables over the United Kingdom for the verification of climate models (Perry & Hollis 2004). Such temperature maps for Pakistan are not available for this purpose therefore, it is necessary to generate these maps by using suitable method of interpolation.

Our aim in this study is to compare the results obtained by: 1) local interpolation approach and 2) the overall multiple regression approach, for establishing surfaces of different temperature variables. However, we deal less with consideration of parameter fitting within each approach and focus instead on differences in performance between the optimal parameter settings from each approach. Instead of using commercial softwares for the purpose of interpolation, a code is written in C++ language, so that this code can be coupled in RCM environment.

Methodology

1. Study Area

Our study area in this work consists of all geographic region of Pakistan, covering an area of 796,095 square kilometers of territory including a wide variety of landscapes, from arid deserts to lush green valleys to stark mountain peaks. Geographically, it can be divided into three regions: the lowlands in the south-east and east, the arid plateau in the southwest, and the mountains of the north as shown in Fig 1. With the complex topography, the climate of the region varies according to elevation. April through September is the most pleasant months in the mountains, although they bring oppressive heat to the low-lying plains of the Indus Valley, where midday temperatures normally exceed 40^0C. December through February are the coolest months, as lowland temperatures drop to 10^0-25^0C and the air temperature in the mountains falls below freezing. Monsoons reach the eastern areas of the country in the late summer and persist during July to September.

2. Data Sources

The data analyzed in this study were obtained from the Pakistan Meteorological Department (PMD). This data set contains monthly mean, minimum and maximum values of temperature for the period 1974-2000 obtained at the 50 stations shown in Fig. 1.

Digital Elevation Model (DEM) data at a resolution of 1000 m obtained from USGS/DAAC HYDRO1k DEM for Asia is used in this study. A mask of Pakistan is generated from USGS/DAAC international boundary coverage.

3. Interpolation Methods

3.1. Inverse Distance Weighting (IDW)

This interpolation method estimates a point using the nearest sample points, which are weighted by a power factor n, proportional to the inverse of their distance from the estimated point. The nearest observation station has the highest weight and the most distant station has lowest weight. Also, higher the power the stronger the influence of the closer sample point. As a constraint, sum of the weights should be equal to 1. The traditional form of this method is

$$P_i = \frac{\sum_{j=1}^{G} P_j / D_{ij}^n}{\sum_{j=1}^{G} 1 / D_{ij}^n}$$

Where, P_i is the value at location *i*, P_j is the value at location *j*, D_{ij} is the distance from *i* to *j* and G is the number of sampled location.

Considering a very low density of meteorological stations, we used a wide range of parameter settings and IDW and IDWEC methods are tested using 3, 5 and 8 neighboring stations. In order to cover a wide range of parameter settings each number of neighbors is tested with powers of 0.5, 1 and 2.

3.2. Inverse Distance Weighting with Elevation Correction (IDWEC)

Pakistan has got a very complex topography starting from sea level in the South to sky scrapping peaks like K2 (8611m) in the North. Under these circumstances, elevation is usually effective predictor of temperate: therefore data has been detrended for elevation before interpolating with IDW. A constant lapse rate has been used since more explicit calculations of lapse rates did not improve interpolation model performance (Dodson & Marks 1997). These lapse rates are calculated by linear regression. The resulting regression equation is used to convert all temperature values to zero elevation temperatures. IDW is then applied to this detrended data. Once this data is interpolated onto the grid, the trend is again added to each pixel of the grid.

3.3. Multiple Regression Models

The predictors used in the regression models are x coordinate (latitude), y coordinate (longitude), xy and elevation. The units of x and y are in meters and elevation is expressed in meters above sea level. Three standard techniques of variable selection used in the multiple regression model which are Backward Elimination, Stepwise Regression and Forced Entry.

3.3.1. Backward Elimination

In this procedure, at first step we compute the regression equation containing all variables, and then at each step we drop a variable on the basis of partial F-test value. If a variable is not significant then we drop it from the equation and recomputed the regression using the remaining variables. This process continues until all variables in the regression are significant.

3.3.2. Stepwise Regression

In this procedure, we start with a regression equation having no variable in the equation. Then first variable enter the equation is the one which has the highest simple correlation with the dependent variable. The next variable is selected according to the highest partial correlation with the dependent variable. The significance of each variable is then checked with the help of partial F-test value. If a variable is insignificant then it is removed from the equation. This process continues until all variables in the equation are significant.

3.3.3. Forced Entry

This procedure is simple as compared to stepwise selection and Backward Elimination because it does not involve calculation of partial correlation or partial F-test value (Norusis/SPSS Inc. 1993). This procedure is sometimes called "enter all". In this method we enter all the predictor variables into the equation at the same time and do not check the partial correlation or F-test value to check which variable we have to enter and which variable we have to remove from the equation. We just run the equation including all the predictor variables and check the p-value of each variable individually. If a variable is insignificant, we drop it from the equation and run the regression equation again by including all significant variables. The results are checked again if any additional variable has became insignificant. This process continues until all predictor variables in the equation are significant.

3.4. Combined Regression-Local Interpolation Approach

Combination of regression models with local methods is also tested. This is done by interpolating the data locally after detrending all topographic and geographic variables according to the regression model. By combining the most effective (best validation test results) local interpolation method and the most effective regression model, this combined method is applied once for each temperature variable.

4. Data Analyses

The data obtained from PMD are used to calculate averaged monthly extremes and seasonal averages. Monthly extremes are calculated using Averaged Monthly Minimum temperature for January (AMMin1) and Averaged Monthly Maximum temperature for June (AMMax6). For seasonal averages, we considered Averaged Mean Seasonal temperature for Summer (AMSS) and Averaged Mean Seasonal temperature for winter (AMSW), representing summer (April-September) and winter (October-March) respectively.

The above mentioned monthly extremes and seasonal averages are interpolated using local techniques as well as regression models which are discussed in the previous sections. Ordinary kriging interpolation method is not used due to the relative scarcity of data, which makes it impossible to calculate the coefficient of semivariogram model with reasonable lag distance (<15km) (Kurtzman & Kadmon 1999).

4.1. Evaluation of Estimated Surfaces

The performance of each of the 21 interpolation procedures described above (9 variants of IDW, 9 variants of IDWEC and 3 variants of regression approach) is evaluated for each temperature variable using a cross validation approach. One station is taken out of the database in each iteration, then a new surface of estimation is constructed for IDW and IDWEC whereas, for regression methods a new model is calculated in each iteration. The estimates of missing data are saved. The largest error, mean error and mean absolute error of estimation are calculated. Values of R^2, between observed and predicted values are also calculated and the results are discussed in the next section.

Results and Discussion

1. Lapse Rates and Regression Models

Elevation predicted mean temperatures better in all the methods except for AMMax6 (Table 1(a)). The addition of the geographic predictors in Stepwise and Forced Entry models explains the variations in temperature better than the previous case, but it does not show any improvement for the case of AMMax6 except for Backward Elimination method which has improved the prediction in AMMax6 (Table 1(b)). It is noticeable that only elevation is entered into forced entry method which makes it similar to lapse rate case (Table 1(a)). Therefore, this method is not discussed afterwards. The variables selected in other two regression methods are given in (Table 1(b)).

2. Evaluation of Model Performance

2.1. Averaged Monthly Minimum Temperature of January (AMMin1)

For AMMin1, the variables for both the regression model is similar and both the regression models produce the lowest mean absolute errors and highest R^2 (Table 2). It is also noticeable that addition of elevation correction in IDW has neither improved the mean absolute error nor R^2. In all the cases, except for simple IDW the choice of parameters in IDW and IDWEC has little effect on mean absolute errors and R^2. Maps for best performing regression (Backward Elimination) and local method (IDWEC (0.5, 8)) are given in Fig 2. Map of IDWEC has shown more pronounced extreme temperature as compared to smoother map of regression model.

2.2. Averaged Monthly Maximum Temperature of June (AMMax6)

In AMMax6, there is very little to choose when it comes to best performing method in validation test. IDWEC (0.5, 3), shows the best mean absolute errors, although not by much when we compare it with best performing regression method which is Backward Elimination method (Table 3). It is obvious that addition of elevation correction in IDW has slightly increased the mean absolute errors but the R^2 values have definitely increased. From Fig 3, it is obvious that IDWEC (0.5, 3) is showing cooler temperatures than Backward Elimination regression map.

2.3. Averaged Mean Seasonal Winter Temperature (AMSW)

For AMSW, the variables for both the regression model are similar and both of them have produced lowest mean absolute errors and highest R^2. It is also interesting to note that addition of elevation correction in IDW has significantly increased the R^2 and reduced the mean absolute errors (Table 4). In maps of AMSW (Fig 4.), IDWEC (0.5, 8) is showing a cooler temperature trend than regression map. In northern areas of Pakistan, where there is a very complex topography, a difference of prediction can be seen between the two methods which will be discussed later.

2.4. Averaged Mean Seasonal Summer Temperature (AMSS)

For AMSS, again there is very little to choose when it comes to the best performing method in validation test. IDWEC with the power 0.5 and 3 nearest neighbors has shown lowest mean absolute error. Addition of elevation correction in IDW once again has shown an improvement in results (Table 5). Map of IDWEC (0.5, 3) is predicting cooler temperature than Backward Elimination regression model (Fig. 5). In the Monson fed area of Pakistan, differences can be seen in both the cases which will be discussed later.

2.5. Combination of a regression model and a local interpolator

The use of local interpolation method after detrending all topographic and geographic variables according to the regression equation is tested once for each variable. The 2 methods combined in each temperature variable are the regression model and the local interpolation method which gave the lowest mean absolute error.

When we compared the validation test results from the combined methods shown in Table 6 with the results of separated methods in Table 2 to 5, we can see that for both winter variables, AMMin1 and AMSW, the combined method did not improve predictions over the best interpolation method in Tables 2 and 4. Whereas for AMMax6 and AMSS, the combined method has improved mean absolute error, maximum error and R^2.

As discussed earlier, for AMSW and AMSS there is a difference present in the maps of best performing local and regression model. In AMSW, the difference is probably due to the effect of westerly disturbances coming from Mediterarian sea and resulting in winter precipitation in Northern Areas of Pakistan. For detailed analysis, the stations in the Northern regions are taken which are given in Table 7(a). Similarly for AMSS, the difference in the two maps is probably due to the effect of Monsoon coming from Bay of Bengal and Arabian sea resulting in summer precipitation. Stations in the monsoon fed area taken for the detailed analysis are given in Table 7(b). For both the cases, the mean absolute error for IDWEC method is low as compared to the regression method. Therefore, it can be concluded that the local interpolation technique is more suitable in cases where there is a short range climate factor involved Table 8.

The maximum error in Tables 2 to 5 can shed some light on the advantages and disadvantages of different methods. In all the cases except for AMSW, in which the temperature patterns are quite smooth, Jiwani station is showing the Maximum Error when interpolating with local methods. This is attributed to the large distances and differences in station elevation of neighboring stations from Jiwani.

Conclusions

We compared the local interpolation approach and the multiple regression approach for each of the 4 temperature variables which are Averaged Monthly Minimum temperature for January (AMMin1), Averaged Monthly Maximum temperature for June (AMMax6), Averaged Mean Seasonal temperature for Summer (AMSS) and Averaged Mean Seasonal temperature for winter (AMSW). None of the individual interpolation approaches proved to be robust with all 4 temperature variables. For two summer variables AMMax6 and AMSS, although IDWEC is performing best but not by much when we compare it with regression method. For winter variables AMMin1 and AMSW, the regression method outplays the performance of local interpolation method. Given the simplicity of regression models and their performance for all the four variables, they can be a preferred choice for the purpose of temperature interpolation in Pakistan.

It can be concluded that the regression models, with topographic and geographical variables are predicting the temperatures better than local interpolation methods. The Backward Elimination method in all 4 cases is outperforming the Stepwise regression method. It will be safe to say that Backward Elimination method is the best for generating girded temperature maps for Pakistan. However, it should be emphasized that the large errors in the analyses of all the interpolation methods are mainly attributed to the low density of meteorological stations which falls short, by more than an order of magnitude, of minimum requirement recommended by WMO (Archer and Fowler 2004).

Table 1. Summary of regressions. (a) The linear lapse rates used for detrending before applying IDWEC. (b) Regression models derived from using all stations. Temperature variables: AMMax6 = Averaged Monthly Maximum temperature in June; AMMin1 = Averaged Monthly Minimum Temperature in January; AMSS = Averaged Mean Seasonal temperature in Summer; AMSW = Averaged Mean Seasonal temperature in Winter

Temperature Variable	Constant (°C)	Lapse Rate (°C \ m)	x	y	xy	R²	p
(a) Elevation Correction							
AMMax6	41.4621	-0.005050	*	*	*	0.5440	< 0.00001
AMMin1	7.5077	-0.005479	*	*	*	0.7574	< 0.00001
AMMS	32.0805	-0.005666	*	*	*	0.8452	< 0.00001
AMMW	20.0696	-0.006720	*	*	*	0.8914	< 0.00001
(b) Regression Models							
Stepwise							
AMMax6	41.4621	-0.005050	+	+	+	0.5440	< 0.00001
AMMin1	3.2228	-0.004289	+	+	1.2E-12	0.8171	< 0.00001
AMMS	27.3279	-0.005323	-1.7E-06	+	+	0.8633	< 0.00001
AMMW	15.0939	-0.005338	+	+	1.4E-12	0.9543	< 0.00001
Backward							
AMMax6	-25.5316	-0.004527	-2.6E-05	-5.4E-05	-2.1E-11	0.6986	< 0.00001
AMMin1	3.2228	-0.004289	+	+	1.2E-12	0.8171	< 0.00001
AMMS	1.9644	-0.004956	-1.1E-05	-2.3E-05	-8.3E-12	0.8864	< 0.00001
AMMW	15.0939	-0.005338	+	+	1.4E-12	0.9543	< 0.00001
Forced Entry							

AMMax6	41.4621	-0.005050	+	+	+	0.5440	< 0.00001
AMMin1	7.5077	-0.005479	+	+	+	0.7574	< 0.00001
AMMS	32.0805	-0.005666	+	+	+	0.8452	< 0.00001
AMMW	20.0696	-0.006720	+	+	+	0.8914	< 0.00001

* : Not Applicable

\+ : Insignificant

Table 2. Cross validation test results for Averaged Monthly Minimum temperature in January (AMMin1) estimates. The parameters in the IDW and IDWEC interpolation are (power, number of nearest stations). The interpolation method that gave the lowest mean absolute error in each method is given in bold.

Method of Interpolation and Parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
IDW(0.5,3)	0.2859	2.1742	-10.3695	Jiwani	0.5239
IDW(0.5,5)	0.2085	2.2354	-9.1052	Jiwani	0.5297
IDW(0.5,8)	0.2932	2.1291	-7.7159	Jiwani	0.5941
IDW(1,3)	0.3099	2.1786	-10.3077	Jiwani	0.5278
IDW(1,5)	0.2782	2.1827	-9.2046	Jiwani	0.5426
IDW(1,8)	0.3135	2.0957	-7.9974	Jiwani	0.6000
IDW(2,3)	0.3419	2.1801	-10.1903	Jiwani	0.5315
IDW(2,5)	0.3698	2.1471	-9.3869	Jiwani	0.5515
IDW(2,8)	0.3650	2.0670	-8.5383	Jiwani	0.5952
IDWEC(0.5,3)	0.1115	2.2103	-6.1089	Jiwani	0.5408
IDWEC(0.5,5)	0.1007	2.1022	-5.2638	Jiwani	0.5774
IDWEC(0.5,8)	0.1139	2.0321	-5.2097	Jiwani	0.5919
IDWEC(1,3)	0.1302	2.2028	-5.9938	Jiwani	0.5431
IDWEC(1,5)	0.1396	2.1071	-5.2805	Jiwani	0.5717
IDWEC(1,8)	0.1323	2.0512	-5.2320	Jiwani	0.5836
IDWEC(2,3)	0.1513	2.1818	-5.7618	Jiwani	0.5454
IDWEC(2,5)	0.1840	2.1010	-5.2804	Jiwani	0.5615
IDWEC(2,8)	0.1714	2.0723	-5.2507	Jiwani	0.5683
AMMin1 Stepwise	0.0047	1.5947	-5.4635	Jiwani	0.7868
AMMin1 Backward	0.0047	1.5947	-5.4635	Jiwani	0.7868

Table 3. Cross validation test results for Averaged Monthly Maximum temperature in June (AMMax6) estimates. The parameters in the IDW and IDWEC interpolation are (power, number of nearest stations). The interpolation method that gave the lowest mean absolute error in each method is given in bold.

Method of Interpolation and Parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
IDW(0.5,3)	0.3168	2.9798	10.4258	Muree	0.3398
IDW(0.5,5)	0.1257	3.1003	11.1980	Muree	0.3477
IDW(0.5,8)	0.2060	2.9257	11.4504	Muree	0.3728
IDW(1,3)	0.3197	2.9790	10.2846	Muree	0.3437
IDW(1,5)	0.1606	3.0476	11.0106	Muree	0.3501
IDW(1,8)	0.1840	2.9227	11.1808	Muree	0.3747
IDW(2,3)	0.3239	2.9810	9.9963	Muree	0.3446
IDW(2,5)	0.2276	2.9918	10.6187	Muree	0.3488
IDW(2,8)	0.2034	2.9264	10.6968	Muree	0.3692
IDWEC(0.5,3)	0.1560	2.0132	10.8907	Jiwani	0.5997
IDWEC(0.5,5)	0.0263	2.1039	8.8248	Jiwani	0.5997
IDWEC(0.5,8)	0.0408	2.1108	7.9102	Jiwani	0.6081
IDWEC(1,3)	0.1540	2.0209	10.7886	Jiwani	0.6075
IDWEC(1,5)	0.0328	2.0773	8.9868	Jiwani	0.6097
IDWEC(1,8)	0.0170	2.0604	8.1760	Jiwani	0.6183
IDWEC(2,3)	0.1482	2.0342	10.5813	Jiwani	0.6195
IDWEC(2,5)	0.0564	2.0536	9.2733	Jiwani	0.6258
IDWEC(2,8)	0.0250	2.0171	8.6866	Jiwani	0.6337

AMMax6 Stepwise	0.0266	2.5550	9.3782	Peshawar	0.4977
AMMax6 Backward	0.0814	2.0517	10.5533	Peshawar	0.6018

Table 4. Cross validation test results for Averaged Monthly Mean Winter Temperature (AMSW) estimates. The parameters in the IDW and IDWEC interpolation are (power, number of nearest stations). The interpolation method that gave the lowest mean absolute error in each method is given in bold.

Method of Interpolation and Parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
IDW(0.5,3)	0.2371	2.1546	7.4480	Astor	0.6520
IDW(0.5,5)	0.1677	2.2465	6.7291	Parachinar	0.6560
IDW(0.5,8)	0.2156	2.1692	7.6722	Quetta	0.6883
IDW(1,3)	0.2454	2.1672	7.4631	Astor	0.6529
IDW(1,5)	0.2078	2.2120	6.7500	Parachinar	0.6594
IDW(1,8)	0.2139	2.1367	7.5662	Quetta	0.6908
IDW(2,3)	0.2500	2.1847	7.4443	Astor	0.6495
IDW(2,5)	0.2573	2.1873	6.8192	Parachinar	0.6567
IDW(2,8)	0.2291	2.1294	7.3677	Quetta	0.6830
IDWEC(0.5,3)	0.0330	1.1979	-3.9661	Kotli	0.9147
IDWEC(0.5,5)	0.0354	1.0848	-4.2198	Kotli	0.9267
IDWEC(0.5,8)	-0.0042	1.0396	-4.4277	Kotli	0.9291
IDWEC(1,3)	0.0249	1.1806	3.9331	Islamabad	0.9168
IDWEC(1,5)	0.0378	1.0906	-4.1496	Kotli	0.9265
IDWEC(1,8)	-0.0083	1.0471	-4.3321	Kotli	0.9289
IDWEC(2,3)	0.0162	1.1624	3.9583	Islamabad	0.9191
IDWEC(2,5)	0.0295	1.1041	-3.9888	Kotli	0.9253
IDWEC(2,8)	-0.0083	1.0732	-4.1289	Kotli	0.9277
AMMW Stepwise	0.0059	0.7690	-4.4663	Kotli	0.9482
AMMW Backward	0.0059	0.7690	-4.4663	Kotli	0.9482

Table 5. Cross validation test results for Averaged Monthly Mean Summer Temperature (AMSS) estimates. The parameters in the IDW and IDWEC interpolation are (power, number of nearest stations). The interpolation method that gave the lowest mean absolute error in each method is given in bold.

Method of Interpolation and Parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
IDW(0.5,3)	0.2810	2.3994	8.7477	Astor	0.4561
IDW(0.5,5)	0.1172	2.4504	7.8681	Muree	0.4607
IDW(0.5,8)	0.1178	2.3135	8.1146	Muree	0.4974
IDW(1,3)	0.2914	2.4140	8.7177	Astor	0.4566
IDW(1,5)	0.1616	2.4324	7.6950	Muree	0.4600
IDW(1,8)	0.1257	2.3336	7.8589	Muree	0.4936
IDW(2,3)	0.3019	2.4384	8.5896	Astor	0.4522
IDW(2,5)	0.2314	2.4335	7.8888	Astor	0.4529
IDW(2,8)	0.1772	2.3691	7.9630	Astor	0.4778
IDWEC(0.5,3)	0.1006	1.1722	6.1313	Jiwani	0.8454
IDWEC(0.5,5)	0.0057	1.2378	5.1381	Jiwani	0.8511
IDWEC(0.5,8)	-0.0676	1.2327	-4.5572	Chilas	0.8603
IDWEC(1,3)	0.1056	1.1888	6.0928	Jiwani	0.8455
IDWEC(1,5)	0.0182	1.2435	5.2231	Jiwani	0.8510
IDWEC(1,8)	-0.0616	1.2338	4.5686	Jiwani	0.8604
IDWEC(2,3)	0.1048	1.2397	6.0092	Jiwani	0.8442
IDWEC(2,5)	0.0393	1.2569	5.3737	Jiwani	0.8495
IDWEC(2,8)	-0.0230	1.2455	4.9086	Jiwani	0.8567

AMMS Stepwise	0.0103	1.3264	5.4397	Jiwani	0.8365
AMMS Backward	0.0245	1.2721	-5.3933	Chillas	0.8499

Table 6. Cross validation test results for combined interpolation method estimates. The parameters in the IDW interpolation are (power, number of nearest stations).

(a) IDW + STEPWISE	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
AMMax6 (0.5,3)	0.1560	2.0132	10.8907	Jiwani	0.5997
AMMin1 (0.5,8)	0.2085	1.8745	8.1704	Peshawar	0.6334
AMMS (0.5,3)	0.1416	1.1815	6.3526	Jiwani	0.8385
AMMW (0.5,8)	0.1056	0.8655	2.6300	Quetta	0.9462
(b) IDW + BACKWARD	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
AMMax6 (0.5,3)	0.1669	2.0104	7.7893	Peshawar	0.6596
AMMin1 (0.5,8)	0.2085	1.8745	8.1704	Peshawar	0.6334
AMMS (0.5,3)	0.1311	1.1299	-4.7642	Chillas	0.8565
AMMW (0.5,8)	0.1056	0.8655	2.6300	Quetta	0.9462

Table 7. Stations used in the analysis of Northern and Monsoon fed areas of Pakistan.

(a) Meteorological stations in Northern Areas	(b) Meteorological stations in Monsoon fed area
Gupis	Saidu Sharief
Gilgit	Balakot
Chitral	Muzaffarabad
Bunji	Kakul
Drosh	Ghari Dupatta
Chilas	Muree
Astor	Kotli
Skardu	Islamabad
Dir	Jehlum
	Sialkot
	Lahore(AP)
	Lahore(PBO)

Table 8. Comparison of cross validation test results for Northern and Monsoon fed areas of Pakistan. The parameters in the IDWEC interpolation are (power, number of nearest stations).

(a) Northern Areas	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
Backward	0.4513	1.0069	2.2739	Astor	0.8891
IDWEC(0.5,8)	-0.0951	0.9811	-2.1937	Chillas	0.8609
(b) Monsoon fed area	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C)	Respective station	Observed/ predicted R^2
Backward	0.6654	1.1786	-2.8459	Kotli	0.8691
IDWEC(0.5,3)	-0.0082	1.0133	-4.0706	Kotli	0.8510

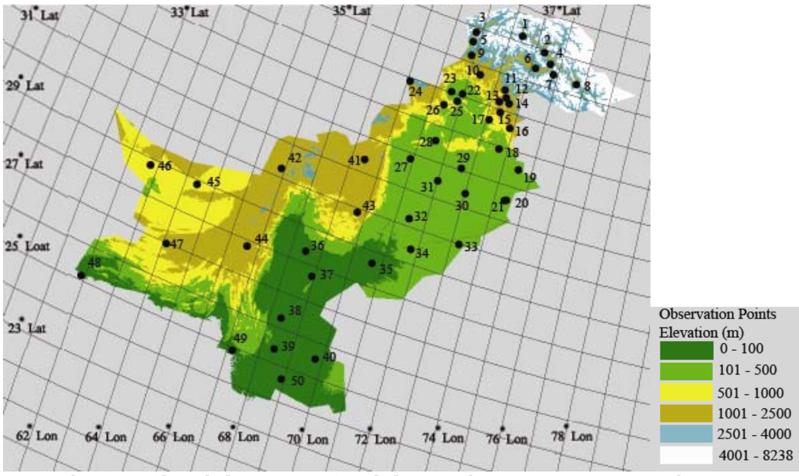
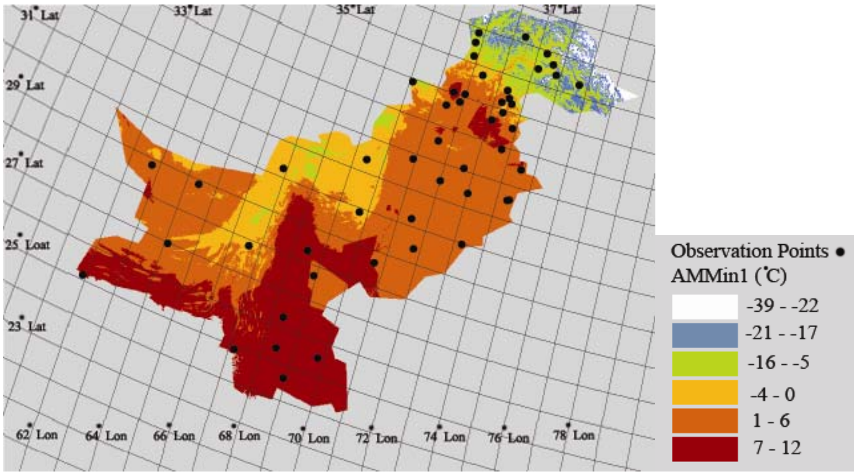


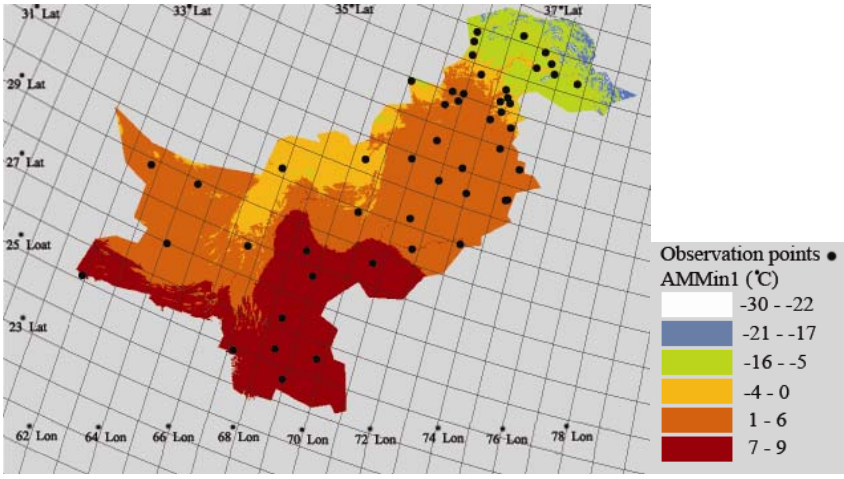
Fig 1. The DEM (digital elevation map) and climatic observation stations in Pakistan

Station	Height	Station	Height
1 - Gupis	(2156)	26- Kohat	(503)
2 - Gilgit	(1460)	27- D I Khan	(174)
3 - Chitral	(1500)	28- Mianwali	(210)
4 - Bunji	(1372)	29- Sargodha	(185)
5 - Drosh	(1465)	30- Faisalabad	(184)
6 - Chilas	(1251)	31- Rafique	(150)
7 - Astor	(2168)	32- Multan	(123)
8 - Skardu	(2210)	33- Bahawalnagar	(162)
9 - Dir	(1370)	34- Bahawalpur	(117)
10- Saidu Sharief	(962)	35- Khanpur	(88)
11- Balakot	(981)	36- Jacobabad	(56)
12- Muzaffarabad	(702)	37- Rohri	(68)
13- Kakul	(1309)	38- Nawabshah	(38)
14- Ghari Dupatta	(813)	39- Hyderabad	(41)
15- Muree	(2168)	40- Chhor	(6)
16- Kotli	(2017)	41- Zhob	(1407)
17- Islamabad	(508)	42- Quetta	(1601)
18- Jehlum	(234)	43- Barkhan	(1098)
19- Sialkot	(253)	44- Khuzdar	(1232)
20- Lahore-AP	(216)	45- Dalbandin	(850)
21- Lahore-PBO	(214)	46- Nokundi	(683)
22- Risalpur	(320)	47- Punjgar	(981)
23- Peshawar	(360)	48- Jiwani	(57)
24- Parachinar	(1729)	49- Karachi(AP)	(22)
25- Cherat	(1302)	50- Badin	(9)

Legends:
A.P = Air Port
P.B.O = Pilot Baloon Observation

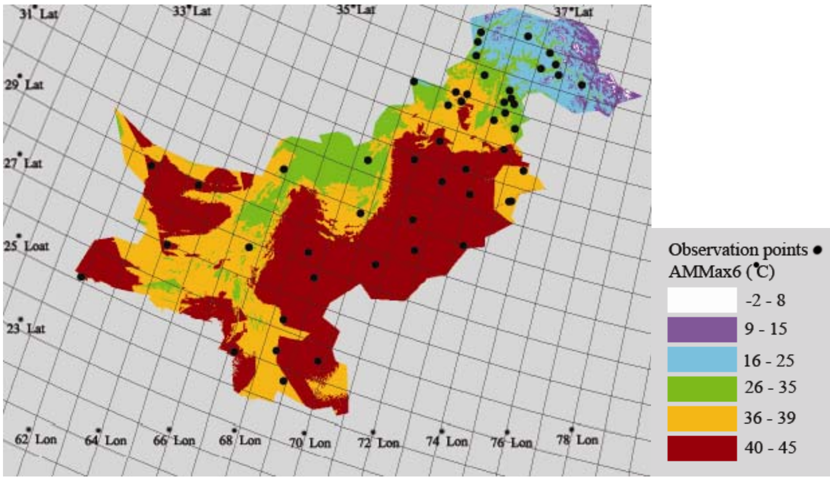


(a)

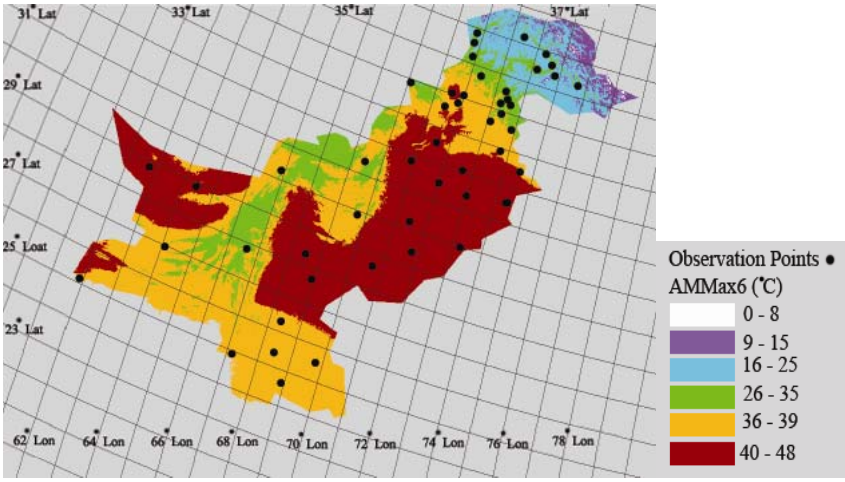


(b)

Fig 2. Averaged Monthly Minimum temperature in January (AMMin1)
(a) IDWEC(0.5,8) method (mean absolute error: 2.03ºC);
(b) The Backward Elimination regression model (mean absolute error: 1.59ºC)

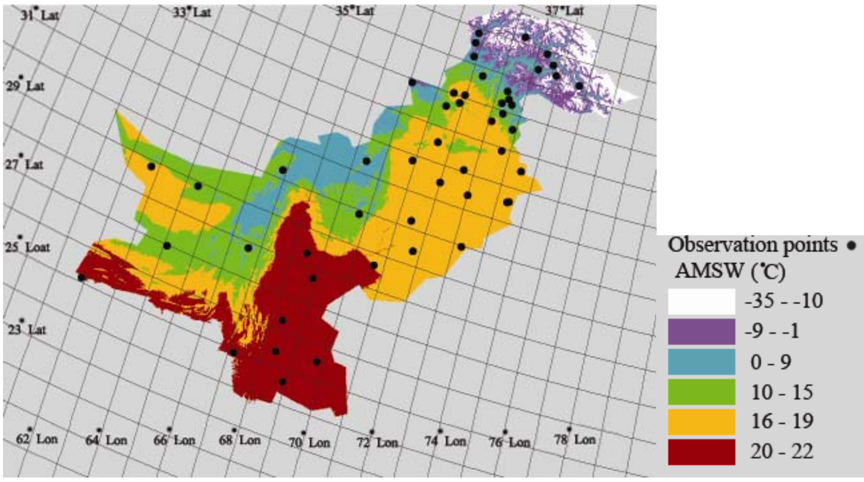


(a)

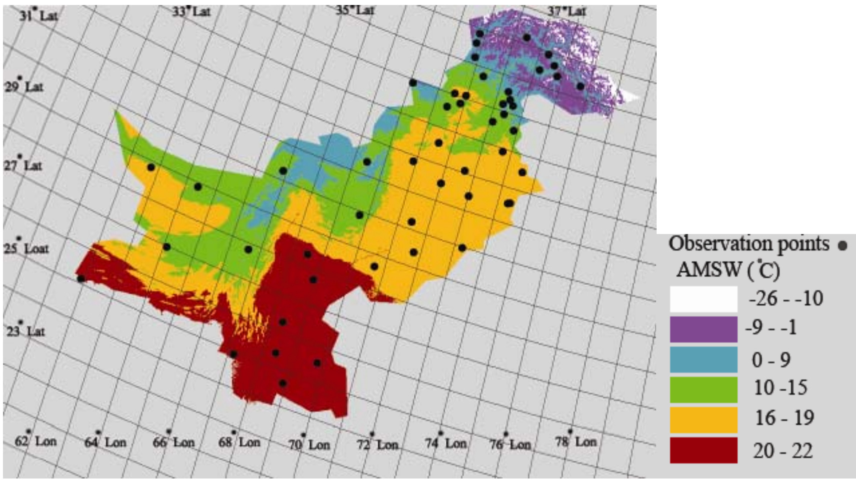


(b)

Fig 3. Averaged Monthly Maximum temperature in June (AMMax6)
(a) IDWEC(0.5,3) method (mean absolute error: 2.01ºC);
(b) The Backward Elimination regression model (mean absolute error: 2.05ºC)

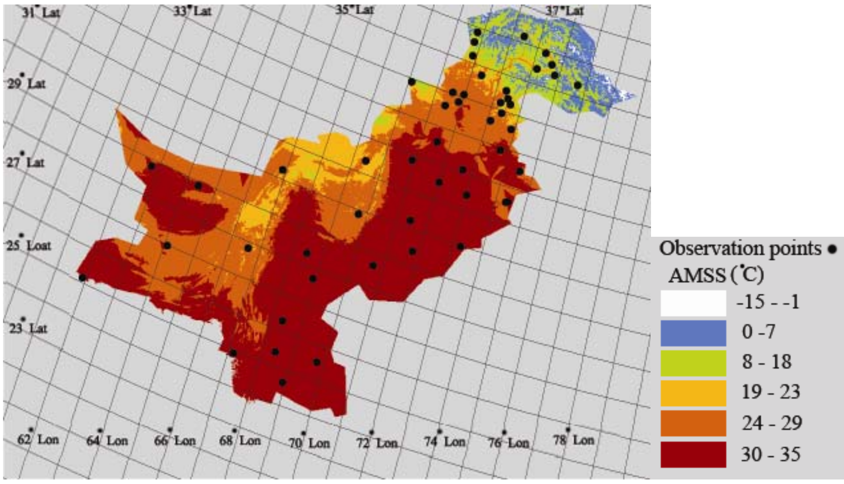


(a)

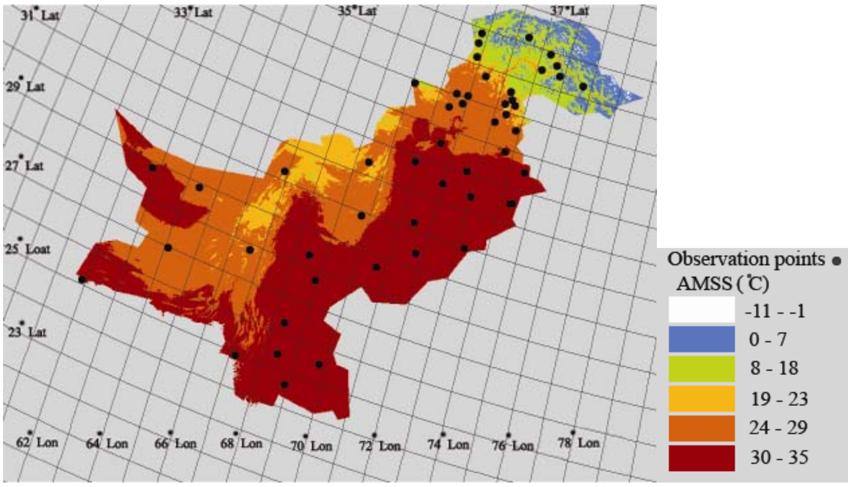


(b)

Fig 4. Averaged Mean Seasonal temperature in Winter (AMSW)
(a) IDWEC(0.5,8) method (mean absolute error: 1.03ºC);
(b) The Backward Elimination regression model (mean absolute error: 0.76ºC)



(a)



(b)

Fig 5. Averaged Mean Seasonal temperature in Summer (AMSS)
(a) IDWEC(0.5,3) method (mean absolute error: 1.17ºC);
(b) The Backward Elimination regression model (mean absolute error: 1.27ºC)

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