The Sub-Regional Classification of Pakistan's Winter Precipitation Based On Principal Components Analysis

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Abstract

Wintertime (December – March, DJFM) rainfall contributes about 30 % to the annual total rainfall of Pakistan with some areas in west and southwest of the country being entirely dependent on winter rains. Winter precipitation plays a pivotal role towards the agriculture, water reservoirs, hydroelectric power generation and ecosystems of the country. Pakistan owing to its peculiar topographic features exhibits a distinctively different spatial rainfall distribution from north to south. In this study 30-year monthly and seasonal (December – March, DJFM) total rainfall data of 35 data sites over a period 1976-2005 have been used to find out spatial rainfall distribution and hence identify the sub-regional rainfall distribution patterns across the country. The Principal Components Analysis (PCA) has been performed to delineate the spatial rainfall variance and pattern from within the data stations which identified the six different spatial rainfall sub-regions within Pakistan.

Key Words: PCA, Pakistan's winter precipitation, sub-regionalization, spatial rainfall variability.

Introduction

Located in the South Asia, Pakistan stretches from latitude 24 °N to 36 °N and longitude 61.5 °E to 76.5 °E. It is bounded by the Arabian Sea in south, India in the east, Iran and Afghanistan in the west and China in the north. It has got a uniquely diverse topography with world famous mountain ranges, the Himalayan, the Karakoram and the Hindu Kush lying in the north and northwest and vast deserts in south, Thar in Sindh, Cholistan and Thal in Punjab with some hill deserts in south-west Balochistan. Geographically three significant regions are lowlands along Indus in the south and east, the arid plateau of Balochistan in southwest and big/ lofty mountains in the north (Figure 1). Pakistan experiences mainly two rainy seasons summer monsoon (July - September, JAS) and winter season (December - March, DJFM) with annual area - weighted rainfall being 238 mm. Of which the summer contribution is 137.5 mm (about 57 %), winter 74.9 mm (about 30 %) and 25.6 mm (13 %) the rest, thunderstorms etc (source: CDPC, PMD). The winter rain plays a pivotal role towards country's main crops like wheat, sugarcane, grams and mustard production and growth with solid precipitation (in form of snow accumulation) over mountain ranges being of crucial importance for socio-economic development of the country.

Figure 1: Pakistan's location and topography (from: Google. maps.com)

Pakistan exhibits distinctively large spatial rainfall variability from south to north with total annual rainfall ranging in 100 mm – 200 mm in the south and 1500 mm – 2000 mm in north/northeast. Similarly the normal (1971 -2000) winter (DJFM) rain variability ranges from as low as 50 -100 mm in south to 550 – 600 mm in the north (Figure 2).

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In Figure 2 the normal winter rainfall distribution across Pakistan with maximum concentration (450-550 mm) in north Pakistan (around Lat 34°N-35°N and Long 72°E-74°E). The minimum of up to 50 mm in south Punjab, Sindh and NW- Balochistan, an ample depiction how large spatial rainfall variation Pakistan exhibits, (Source: CDPC).

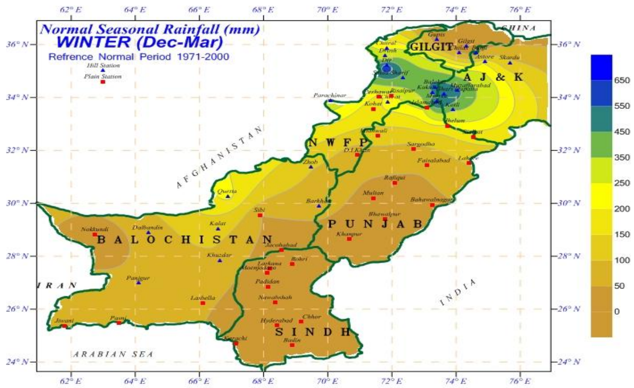

Figure 2: The normal winter rainfall distribution across Pakistan

A classification of rainfall regions across an area is considered to be essential for understanding the rainfall distribution patterns across the area. The studies have demonstrated that the local climatic variability associated with each particular station does not reflect the regional change (Rossel et al. 1999; Rossel and Garbrecht, 2000). The WMO (2000) also emphasizes the importance of spatially integrated climate as it provides more pertinent information on climatic variability as compared to that of single station which is of local featured "weather". Pakistan's distinctly large spatial rain variability from south to north poses an impediment to any study of understanding the rainfall variability or rainfall patterns (and consequent potential climatic signal emergence) over whole Pakistan as a single unit or on individual station basis, and hence requires the data stations be grouped into some regionalized/ sub-regionalized pattern. The desired sub-regionalization or rainfall-based classification would also be helpful for the region-level planning for agriculture, water management, ecosystems protection measures and hydroelectric power generation (for which winter season precipitation plays a crucial role).

Rainfall-based classification and sub-regionalization made by various researchers across the globe is mainly done through the Principal Component Analysis (PCAs) or factors (Principal Components, PCs) extraction method because PCA is considered to be the robust way for a sub-division of an area through factors extraction independent of the geographical features associated with data sites from the large datasets. Hussain and Lee (2009) have used the factor and cluster analysis technique to delineate a classification of rainfall regions across Pakistan by considering 10-days rainfall parameter and found the six groups within the rainfall region. Haroon and Rasul (2009) applied the Principal Component Analysis (PCA) on summer rainfall and outgoing long-wave radiation across Pakistan to identify the major oscillations mode present in the data. For the western Iran, where like Pakistan's winter rains, the dominant rainfall activity is due to the mid-latitude eastward moving cyclones, Raziei et al., 2008 identified five spatially homogenous sub-regions on the basis of PCAs. Singh and Singh (1996) computed the principal components (PCs) and varimax rotated principal components (RPCs) of monthly and seasonal monsoon rainfall across the sub-Himalayan region and Gangetic plains and have delineated the 4 distinct homogeneous sub-regions of the same rainfall variability. Gadgil and Joshi (1980) applied a principal component analysis to the mapping of the climate of India using precipitation data.

Jayawardene et al., (2005) used the PCA to classify the spatial rainfall regions and identified the two dominant rainfall regions, wet and dry zones across Sri Lanka. For Switzerland Baeriswyl and Rebetez (1997) determined respectively the 7 and 13 spatially distributed precipitation regions by applying the PCA and cluster analysis to two sets of precipitation data of 47 stations and 101 stations. Martin (1987) using the PCA on correlation matrices of precipitation data of Austria for summer and winter half-year totals for 30-year period showed that Austria can be subdivided into three regions. Williamson and Masterton (1983) used the PCA along with Turc's climatic index of agricultural potential for ecological land classification and delineated three mapped ecological land regions across Alberta, Canada. Kolivras and Comrie (2007) delineated the Hawaii into nine regions on the basis of PCA applied to 124 stations for 30-year period. Diem (2006) by using 13-day precipitation totals from 1953 to 2002 showed that a PCA-based regionalization resulted in three distinct regions across southeast USA. Comrie and Glenn (1998) used the PCA for monthly precipitation of the United States-Mexico border and determined the 9 consistent and contiguous precipitation regions for a large and climatologically complex area. Pineda-Martínez et al., (2007) distinguished the 3 principal geographical regions along northern México by applying the PCA on monthly precipitation and temperature data.

Rationale behind PCA-Based Sub-Regionalization

To observe the rainfall distribution pattern across Pakistan (annual or seasonal - monsoon and/or winter) a generally perceived conception is to sub-divide Pakistan into northern and southern halves. Hanif et al., (2013) used such sub-division technique to investigate the precipitation changes and trends of Pakistan's annual rainfall. And also the sub-division of Pakistan, say in four sub-divisions, merely on latitudinal basis does not seem befitting due to largely different climatic-featured individual data stations and their topography. So to identify the winter spatial precipitation distribution patterns such schemes do not seem appropriate because of a distinctly different response to annual and seasonal rainfall and different climatic features from south to north of the country. So it seems more appropriate and feasible to identify the precipitation distribution patterns on sub-regional scale based on some robust method like PCA as did the numerous researchers around the globe (ref. introduction above).

Data and Methodology

The daily rainfall (mm) datasets of 35 stations, well distributed across Pakistan, for 30- year period (1976–2005) have been collected from the Pakistan Meteorological Department's climate data processing centre (CDPC). The 30-year time span is selected because it conforms to the World Meteorological Organization (WMO) criteria that a 30-year time characterizes the climate of a particular region. Of 35 data sites 23 are from hill/ mountain regions, five are located along the south/south-west coast and rest are from the lowland plain with 19 sites located to the north of 31° N and the remaining (16 sites) located south of 31° N, showing nearly-even distribution of sites and dividing the country in north and south Pakistan (Figure 4b). More information on stations' location, elevation, mean winter rain, mean minimum and maximum temperatures is given in Table-A (Annex-I). The quality-control of data was done by using the EXCEL. Daily data were then aggregated into monthly and seasonal (December-March, DJFM) total rainfall to undertake the factor analysis or principal components analysis (PCA) to delineate the sub-regional division across Pakistan by structure detection within the datasets.

Primarily the PCA is used for data reduction (by removing the redundant variables) or structure detection by examining the underlying relationship between the variables. It does so with a method of transforming the number of correlated variables into small number of uncorrelated variables called the principal components. The main objective of PCA is to reduce the dimensions of the dataset and to identify the new underlying or latent variables. The principal components method of extraction begins by finding a linear combination of variables (a component) that accounts for as much variation in the original variables as possible. It then finds another component that accounts for as much of the remaining variation as possible and is uncorrelated with the previous component, continuing in this way until there are as many components as original variables. Usually, a few components thus account for most of the variation, and these components can be used to replace the original variables. This method is most often used to reduce the number of variables in the data file (Bryan, 1994).

Though the data reduction feature of PCA does not seem very much relevant in this case due to datasets used here (of only 35 stations, treated as 35 variables in PCA) not being too large but the structure detection within the data used is what the prime purpose of this study is. So the PCA is undertaken by using the Statistical Package for Social Sciences, SPSS (Nie, 1968) on both the seasonal and monthly total rainfall of 35 data sites for a 30-year period for factors (or Principal Components) extraction. The 35 stations rainfall (seasonal and monthly total) data are actually our initial input variables on which the PCA is applied which has extracted the 7 principal components (PCs) or factors (Table-B, Annex-I) by extraction method showing 70 % - 91 % variance accounted for on seasonal and 52 % - 87 % variance accounted for on monthly total rainfall. For determination of which eigenvectors are adequate to be retained in the analysis, the Kaiser (1959) criterion (to accept only those principal components with an eigenvalue greater than 1, Table-1) and the 'scree test' proposed by Castell, 1966 is used.

Results and Discussion

The PCA performed on seasonal (DJFM) as well as monthly total rainfall data by a factor analysis method in SPSS (Nie, 1968) has extracted seven principal components of which the first two components on steep slope (Figure 3) with maximum variance accounted for are chosen for solution, Castell (1996). The scree plot of eigenvalues and the component numbers (Figure 3) help to determine the optimal number of components with components on steep slope (components 1 and 2) are extracted and those on shallow slope are not considered because they contribute little to the solution.

In Figure 3 the components on the steep slope (here the 1st two) accountings for the maximum variance in the data have been chosen. The rest of components on the shallow slope contributing little are discarded.

The initial eigenvalues explaining the percent variance, cumulative variance and extraction of sums of squared loadings of the 7 PCs is shown in Table-1.

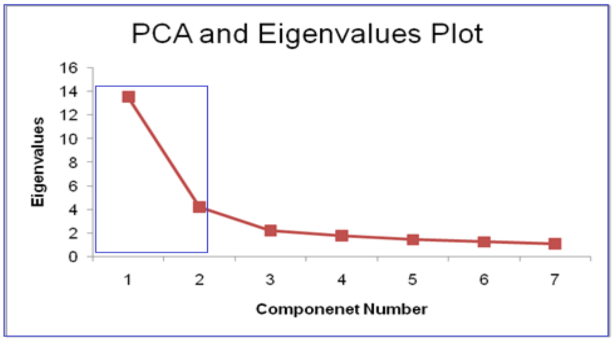

Figure 3: The scree plot of eigenvalue of each component and 7 extracted principal components.

Table 1: The Eigenvalues and variance explained by seven PCs.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	13.566	38.759	38.759	13.566	38.759	38.759
2	4.212	12.033	50.792	4.212	12.033	50.792
3	2.200	6.286	57.078	2.200	6.286	57.078
4	1.773	5.065	62.143	1.773	5.065	62.143
5	1.447	4.135	66.278	1.447	4.135	66.278
6	1.253	3.580	69.858	1.253	3.580	69.858
7	1.081	3.087	72.945	1.081	3.087	72.945

Table-1 shows the eigenvalues (considered those with values > 1, according to the Kaiser Criterion) of the 7 PCs and their explanatory capability for the monthly total rainfall data of 35 data stations. For each component the eigenvalue measures the variance accounted for by the component in all the variables with about 39 % variance accounted for by the PC1, 12 % by the PC2 and then reducing gradually for the rest. The cumulative percentage variance of the 7 PCs is about 73 % both in initial eigenvalues and extracted sums of squared loadings.

The PC1 and PC2 (of both seasonal and monthly total rainfall) are then biplotted to see how data stations cluster together to depict the rainfall distribution pattern within the datasets used. The biplot (or scatter plots) of 1st two PCs on seasonal total with Axis 1 accounting for variance up to 90 % and Axis 2, the 7.6 % of the structure in the dataset identifies the stations' clustering (not shown) which is not contiguous and coherent because most of the data stations depict a scattered spread except few groupings. Consequently this was not considered appropriate. PCA was then performed on monthly total rainfall data which also extracted the seven components of which the biplots of the first two PCs with Axis 1 accounting for 83 % variation and Axis2 the 5.7 % identify the six groups of stations depicting a contiguous and well coherent grouping or clustering apparently due to a larger quantity of the dataset used in the later case and denoted by the Area-I to Area-VI (Figure 4). Here one station Peshawar, lying as an outlier does not cluster with any of group and ultimately on basis of its variance (0.414 on Axis1 falling in the range of Area-I's variance) accounted for is placed in the Area-I. In essence the PCA used to identify the patterns in the monthly total precipitation data did show how the climate series at different stations correlate (Figure 4).

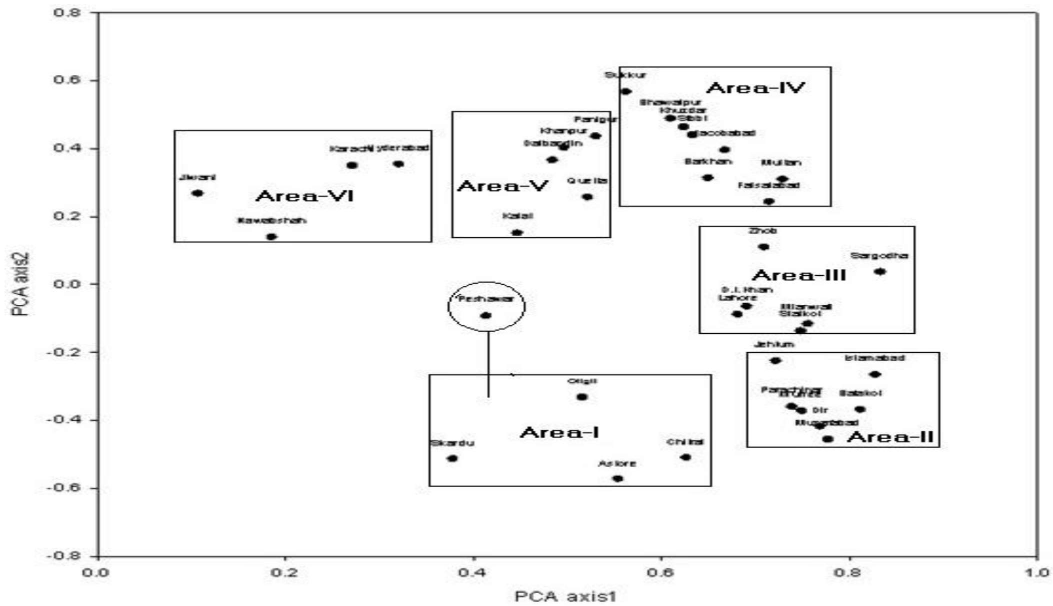

Figure 4: The biplot of 1st two PCs (Axes 1 & 2) on monthly total rainfall with black dots representing the data sites labeled with their names depicts a better coherent and contiguous grouping/ clustering of stations except the Peshawar (small circle in the middle) which according to its variance has been placed in Area-I. The PCA-based clustering of 35 data stations therefore identify the six sub-regions or areas (marked by the rectangles and squares within the Figure) across Pakistan.

For identifying a structure within the dataset used the factor loadings were rotated by varimax rotation method and the result in the form of first two PCs accounting for maximum variance in the dataset is given in Table-2. Factor loadings actually reflect a correlation between input variables and extracted principal components. The PC1 has large positive loadings on the data sites Sargodha, Islamabad, Balakot, Muzaffarabad, Dir, Mianwali, lying in the sub-northern area of Pakistan, and then gradually reducing down the column PC1. The PC2 explains the maximum factors loading (from bottom to top of the column 4) for the southern Pakistan.

Table 2: The rotated factor loadings with 1st two Principal Components (PCs) of monthly total rainfall

S. No	Data Stations	PC1	Data Stations	PC2
1	Sargodha	0.833	Astor	-0.573
2	Islamabad	0.828	Skardu	-0.511
3	Balakot	0.812	Chitral	-0.507
4	Muzafarabad	0.778	Muzafarabad	-0.456
5	Dir	0.769	Dir	-0.419
6	Mianwali	0.756	Murree	-0.373
7	Murree	0.749	Balakot	-0.369
8	Sialkot	0.748	Parachinar	-0.36
9	Parachinar	0.739	Gilgit	-0.32
10	Multan	0.729	Islamabad	-0.266
11	Jehlum	0.722	Jehlum	-0.225
12	Faisalabad	0.715	Sialkot	-0.137
13	Zhob	0.71	Mianwali	-0.117
14	D.I.Khan	0.691	Peshawar	-0.093
15	Lahore	0.682	Lahore	-0.089
16	Jacobabad	0.668	D I Khan	-0.065
17	Barkhan	0.65	Sargodha	0.036
18	Sibbi	0.634	Zhob	0.109

19	Chitral	0.627	Nawabshah	0.139
20	Sibbi	0.624	Kalat	0.151
21	Bhawalpur	0.61	Faisalabad	0.243
22	Sukkur	0.563	Quetta	0.256
23	Astore	0.552	Jiwani	0.267
24	Panjgur	0.531	Multan	0.309
25	Quetta	0.522	Barkhan	0.313
26	Gilgit	0.514	Karachi	0.349
27	Khanpur	0.496	Hyderabad	0.354
28	Dalbandin	0.485	Dalbandin	0.366
29	Kalat	0.447	Jacobabad	0.395
30	Peshawar	0.414	Khanpur	0.402
31	Skardu	0.374	Panjgur	0.436
32	Hyderabad	0.321	Sibbi	0.439
33	Karachi	0.272	Khuzdar	0.463
34	Nawabshah	0.186	Bhawalpur	0.488
35	Jiwani	0.107	Sukkur	0.567

The PC1 factor loadings shown in different colours discern the six different sub-regions of rainfall distribution. To have a graphical view of the two PCs factor loadings are plotted as depicted in Figure 5(a-b).

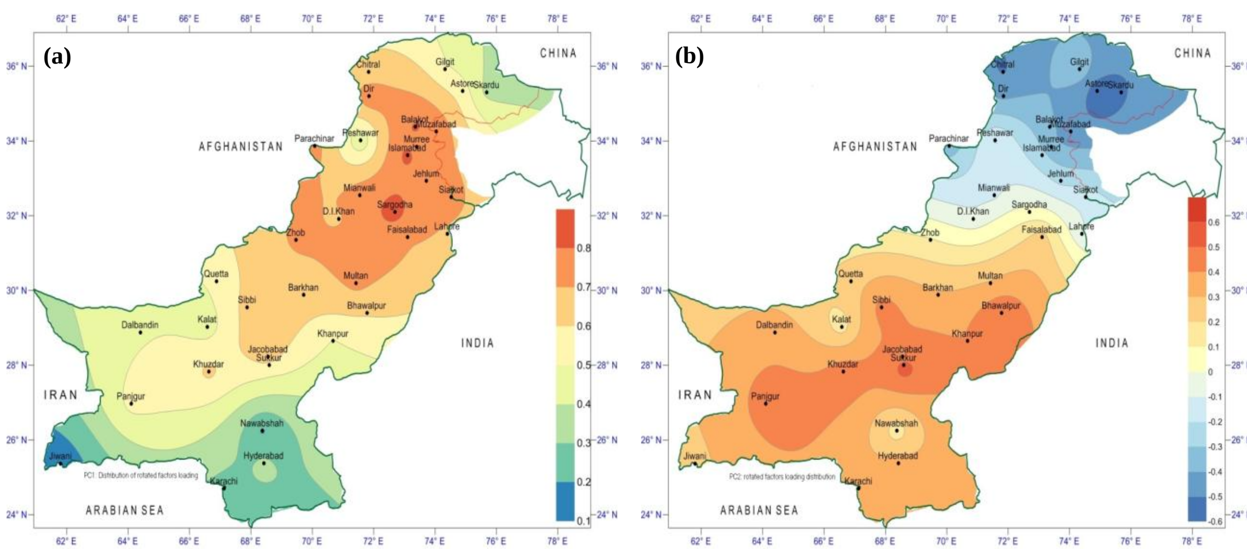

Figure 5: (a) PC1 factor loadings distribution with maximum loadings (0.7-0.8) in the north and minimum (0.1-0.3) in south discerning the different regions across Pakistan.**(b)** PC2 factor loadings distribution; contrary to Figure 5a the +ve loadings in south and –ve in the north Pakistan.

The information on geographical location, number of stations therein, mean winter seasonal rainfall and standard deviation of each identified area is shown in Table-3

Table 3: Location information of PCA- based 6 areas/sub-regions of Pakistan with number of data stations, mean winter rain and standard deviation. *One site Peshawar being an outlier has been re-allotted to Area-I.

Area	**Location**		**No of stations**	**Mean winter rain (mm)**	**Standard deviation (mm)**
	Latitude (°N)	Longitude (°E)			
Area-I	35 - 37	72 - 76	5	147.5	86.2
Area-II	33.4 – 35.1	70 – 74.1*	6	423.8	48.6
Area-III	31 – 33	69.3 - 75	7	95.4	62.3
Area-IV	27 – 30.5	64 - 70	7	85.5	49.7
Area-V	27.2 – 31.2	68.1 - 74	6	33.8	26.2
Area-VI	24.5 – 26.2	62 – 68.2	4	35.9	24.5

Table-3 shows that four data stations group together within the Area-I and becomes 5 in total by placing Peshawar in it. The Area-II and Area-V have six stations each, Area-III and Area-IV contain seven data stations each and Area-VI has four data stations with significantly different averaged winter rainfall ranging from 33.8 mm (Area-V) to about 423.8 mm (Area-II). These six areas are therefore more robust sub-regions within Pakistan which can be used to study the rainfall variability and its impacts on regional basis instead of a vague consideration on whole Pakistan basis.

Conclusion

The application of the Principal Components Analysis (PCA) on 30-year winter monthly total (DJFM) rainfall of 35 data sites has delineated the six sub-regions across Pakistan (Figure 4 and Table-2) which is the robust sub-regional classification of winter rainfall. These results conform to earlier such study conducted by Hussain and Lee (2009) that have also delineated six groups within the rainfall region by considering 10-days rainfall parameter and the normal (1971-2000) winter rainfall distribution of Pakistan. This PCA-based sub-regional classification of winter rains can be of some contribution to study the rainfall trends, climate variability and its impact thereon and rainfall linkages with distant oceanic oscillations like ENSO (El Nino Southern Oscillation), NAO and SSTs-sea surface temperatures which in turn can better provide suggestions and measures for agriculture, water conservation and forecast accuracy at Pakistan's each sub-region level.

This study was based on wintertime rainfall of Pakistan’s 35 data stations for 30-year period. Future plan is to augment it with inclusion of data from more sites and over longer periods, for instance, over 50-60 years. And to vindicate the results the summer monsoon rainfall and temperatures across Pakistan will be subjected to the PCA for such sub-regional classifications.

Acknowledgement

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Annex-I

Table-A: Information of the Meteorological stations used in study (different colours represent different sub-regions) presenting summary information of the stations, the WMO index number, location, elevation, mean winter rain, mean minimum and maximum temperatures (source: CDPC, PMD).

No	Name of Station	WMO Index Number	Region	Elevation a. s. l (m)	Lat.(°N)	Long.(°E)	Mean winter rain (mm)	Mean Temp. (T_{min} °C)	Mean Temp.(T_{max} °C)
1	Chitral	41506	Area I	1499	35° 51'	71° 50'	248.3	1.0	34.1
2	Gilgit	43516	Area I	1459	35° 55'	74° 20'	26.7	0.1	34.3
3	Astore	43520	Area I	2167	35° 22'	74° 54'	193.0	-4.6	25.4
4	Skardu	43517	Area I	2209	35° 18'	75° 41'	99.3	-4.2	29.5
5	Dir	41508	Area II	1369	35° 12'	71° 51'	616.9	-0.4	30.7
6	Balakot	41536	Area II	980	34° 23'	73° 21'	518.2	4.1	32.5
7	Peshawar	41530	Area II	359	34° 01'	71° 35'	170.4	6.6	37.0
8	Parachinar	41560	Area II	1725	33° 52'	70° 05'	270.6	0.7	26.5
9	Islamabad	41571	Area II	507	33° 37'	73° 06'	256.7	5.2	35.2
10	Murree	41573	Area II	2167	33° 55'	73° 23'	518.6	1.8	22.5
11	Muzaffarabad	43532	Area II	701	34° 22'	73° 29'	361.8	5.5	35.0
12	Jehlum	41598	Area III	232	32° 56'	73° 43'	174.7	7.7	36.8
13	Sialkot	41600	Area III	251	32° 30'	74° 32'	170.2	7.5	36.0
14	Lahore	41640	Area III	213	31° 33'	74° 20'	105.7	8.9	36.9
15	Sargodha	41594	Area III	187	32° 00'	72° 07'	21.0	6.9	----
16	Mianwali	41598	Area III	209	32° 35'	71° 32'	27.7	---	---
17	D.I.Khan	41624	Area III	173	31° 49'	70° 55'	62.7	5.9	38.6
18	Zhob	41620	Area III	1405	31° 21'	69° 28'	105.6	2.3	35.2
19	Quetta	41660	Area IV	1600	30° 15'	66° 53'	191.2	-1.0	34.3
20	Barkhan	41685	Area IV	1097	29° 53'	69° 43'	73.4	4.7	35.3
21	Sibbi	41697	Area IV	133	29° 33'	67° 53'	44.8	9.0	42.6
22	Kalat	41696	Area IV	2015	29° 02'	66° 35'	83.2	-1.8	-----
23	Dalbandin	41712	Area IV	848	28° 53'	64° 24'	60.7	4.5	40.3
24	Khuzdar	41744	Area IV	1231	27° 50'	66° 38'	88.5	5.9	36.0
25	Panjgur	41739	Area IV	980	26° 58'	64° 06'	57.6	6.3	38.1
26	Faisalabad	41630	Area V	183	31° 26'	73° 06'	65.9	7.2	37.5
27	Multan	41675	Area V	122	30° 12'	71° 26'	43.1	7.8	39.4
28	Bhawalpur	41700	Area V	116	29° 24'	71° 47'	29.9	8.6	39.6
29	Khanpur	41718	Area V	87	28° 39'	70° 41'	18.7	7.4	39.8
30	Sukkur	41724	Area V	66	27° 42'	68° 54'	21.0	11.3	40.7
31	Jacobabad	41715	Area V	55	28° 18'	68° 28'	24.2	10.8	40.6
32	Nawabshah	41749	Area VI	37	26° 15'	68° 22'	9.3	9.0	40.8
33	Hyderabad	41764	Area VI	40	25° 23'	68° 25'	12.2	13.9	38.5
34	Karachi	41780	Area VI	21	24° 54'	67° 08'	31.9	13.1	33.5
35	Jiwani	41756	Area VI	56	25° 04'	61° 48'	90.9	15.8	32.6

Table-B: Principal Components Matrix

Data stations	Component						
	1	2	3	4	5	6	7
Islamabad	.828	-.266	-.211	-.007	.221	-.022	-.001
Peshawar	.414	-.093	-.231	-.329	-.084	.078	.458
Muzafabad	.778	-.456	.072	.105	.084	-.034	-.175
Parachinar	.739	-.360	.180	-.021	-.279	.114	-.152
Balakot	.812	-.369	.085	.019	.041	.058	.014
Dir	.769	-.419	.190	.011	-.093	.124	-.115
Murree	.749	-.373	-.101	.069	.160	-.020	-.198
Astore	.552	-.573	.074	.236	-.117	-.150	.097
Skardu	.374	-.511	.175	.330	-.115	-.440	.032
Gilgit	.514	-.320	.094	.269	-.196	-.036	.559
Chitral	.627	-.507	.267	.152	-.176	.028	-.023
Lahore	.682	-.089	-.413	-.085	.190	-.032	-.033
Sialkot	.748	-.137	-.367	-.042	.274	-.205	-.074
Jehlum	.722	-.225	-.375	-.042	.327	-.034	-.082
Sargodha	.833	.036	-.216	-.147	.052	.055	.069
Mianwali	.756	-.117	-.036	-.242	-.013	.173	.056
Quetta	.522	.256	.287	-.038	.452	.010	.115
Zhob	.710	.109	.260	-.217	-.043	.280	.118
Kalat	.447	.151	.431	.044	.134	-.331	-.165
Sibbi	.634	.439	.255	-.229	-.168	-.170	-.130
D.I.Khan	.691	-.065	.162	-.231	-.101	.352	-.054
Barkhan	.650	.313	.231	-.172	-.174	.112	-.208
Jiwani	.107	.267	.362	.065	.644	.088	.036
Panjgur	.531	.436	.365	.234	.073	-.065	.264
Dalbandin	.485	.366	.389	.029	.203	-.085	.301
Khuzdar	.624	.463	.280	.089	-.128	-.100	-.195
Multan	.729	.309	-.095	-.177	-.192	.168	.003
Faisalabad	.715	.243	-.339	-.183	.033	-.024	.189
Bhawalpur	.610	.488	-.190	.061	-.246	-.241	.043
Khanpur	.496	.402	-.228	.072	-.005	-.177	-.149
Karachi	.272	.349	-.351	.518	-.105	-.062	.125
Hyderabad	.321	.354	-.106	.528	-.086	.453	-.029
Nawabshah	.186	.139	-.134	.645	.154	.411	-.125
Sukkur	.563	.567	-.225	.025	-.140	-.196	-.052
Jacobabad	.668	.395	-.108	.076	-.151	-.042	-.088

Extraction Method: Principal Component Analysis.
7 components extracted.