

Seasonal Climate Variability in Kullu District, Himachal Pradesh: A Principal Component Analysis

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ABSTRACT

Climate variability poses significant challenges to water resources, agriculture, and ecological stability in mountain regions. This study examines long-term seasonal climate variability in the Upper Beas Basin of Himachal Pradesh using precipitation and temperature data for 1981–2024. Standardised seasonal indices were analysed using Principal Component Analysis (PCA) to identify dominant patterns of climatic covariability across winter, pre-monsoon, monsoon, and post-monsoon seasons. The findings reveal pronounced seasonality and substantial interannual variability in both precipitation and temperature. Monsoon precipitation generally recorded the highest seasonal mean values, while winter and pre-monsoon precipitation exhibited considerable year-to-year variation. Temperature patterns also differed across seasons, with several recent monsoon seasons being comparatively warm and a pronounced post-monsoon warm anomaly occurring in 2024. PCA identified three principal components explaining 69.63% of the total variance. The first component represented warmer winter and post-monsoon conditions associated with lower post-monsoon precipitation, while the second captured non-monsoon precipitation variability alongside cooler pre-monsoon temperatures. The third reflected monsoon precipitation–temperature covariability. These findings demonstrate the value of jointly examining seasonal temperature and precipitation patterns. The study provides a basis for climate-sensitive water resource management, agricultural planning, and adaptation strategies in the Upper Beas Basin and other mountain regions.

Keywords: Seasonal Climate Variability; Upper Beas Basin; Principal Component Analysis; Temperature; Precipitation; Western Himalayas

INTRODUCTION

Climate variability and change in the climate system present one of the greatest threats to global agricultural systems, food security, and socio-economic stability (Thornton et al., 2014). Climate variability refers to short-term and seasonal fluctuations in climatic conditions, including extreme climate events, whereas climate change refers to long-

term, directional changes in patterns of temperature, precipitation, and atmospheric composition (Salinger, 2005). Understanding the relationship between climate variability and climate change is imperative because, over millennial timescales, natural climatic variability has altered the functioning of ecosystems and societies (National Research Council, 1996). Climate variability and change have become central concerns in scientific research, public policy, and development planning, particularly in mountain regions such as the Western Himalayas. The Upper Beas Basin in Himachal Pradesh is an important Himalayan watershed that is increasingly experiencing climate-related variability and extreme weather events, posing risks to ecological stability and human security. Evidence of accelerated glacial melt, unpredictable rainfall, and an increasing incidence of hydro-meteorological disasters highlights the growing vulnerability of the region (Allen et al., 2018; Kumar & Rao, 2021). These challenges also reveal an important research gap in assessing climate-related risks across diverse terrain, microclimatic conditions, and varying levels of socio-economic vulnerability (Dilling et al., 2015; Thakur & Kumar, 2025). Furthermore, the importance of the basin in ensuring water security, supporting hydropower generation, and sustaining the livelihoods of mountain communities makes an understanding of its climatic conditions particularly significant (Pandey et al., 2018).

The Beas River Basin is characterised by steep elevation gradients and pronounced seasonal and spatial variations in precipitation. Understanding long-term patterns of temperature and precipitation is therefore essential for water resource management, agriculture, and environmental planning (Kumar & Rao, 2021; Rani, 2023). The relationship between temperature and precipitation warrants particular attention. While analysing these variables separately provides insights into their individual behaviour, a joint analysis can identify combinations of warmer or cooler and wetter or drier conditions. Seasonal analysis is particularly important because annual summaries may conceal contrasting climatic patterns within different periods of the year. In the present study, climatic variability refers to interannual variation within each season and is distinguished from statistically established long-term climatic trends. Therefore, the purpose of this study is to evaluate long-term seasonal climate variability using temperature and precipitation indices for the period 1981–2024 in the Upper Beas Basin.

LITERATURE REVIEW

Previous research has examined climatic variability at different spatial and temporal scales within the Beas Basin. Rani and Sreekesh (2018) investigated temperature and rainfall variability in the Upper Beas Basin, while Rani (2023) provided a broader

assessment of climate variability. Kumar and Rao (2021) analysed long-term temperature and precipitation records for the larger Beas River Basin. These studies establish relevant regional context, but their study boundaries, datasets, and periods should not be treated as identical to those of the present analysis.

More recent work has used gridded climate datasets and modelling approaches. Tanuja and Kumar (2025) examined temperature and precipitation using TerraClimate data. Patel and Tripura (2022) downscaled large-scale atmospheric variables to investigate local climatic conditions and their potential implications. Barbhuiya et al. (2025) combined regional climate modelling with a hydrological model to assess hydroclimatic responses. These approaches illustrate the distinction between describing historical climate variability and modelling hydrological impacts; the present PCA does not perform the latter.

Multivariate analysis provides a complementary way to summarise climatic relationships. Tadić et al. (2019) applied PCA in climate assessment, and Cai et al. (2023) analysed temperature, precipitation, and related indicators in the middle reaches of the Yangtze River Basin. These studies support the use of PCA as an analytical tool rather than establishing that its application is novel in itself. Kulkarni et al. (2025) compared individual drought indicators with a combined indicator incorporating precipitation, temperature, vegetation, and soil moisture. Their results motivate integrated assessment, but they do not demonstrate that a two-variable seasonal PCA measures socio-economic drought impacts.

The contribution of this study is a joint assessment of eight seasonal temperature and precipitation anomaly series over 1981–2024. PCA summarises dominant covariance patterns, while annual component scores describe when the corresponding combinations occur within the record (Abdi & Williams, 2010; Jolliffe & Cadima, 2016). This complements individual seasonal descriptions without assuming that loadings establish temporal trends, climate drivers, or hazard outcomes.

STUDY AREA

The Upper Beas Basin lies in the western Indian Himalayas of Himachal Pradesh and includes high-altitude headwaters and lower valley environments. Its varied terrain and climatic conditions make it a relevant setting for examining seasonal temperature and precipitation variability. The basin supports water-dependent livelihoods and infrastructure. Regional risk assessments underline the need to distinguish climatic conditions from exposure and vulnerability (Allen et al., 2018).

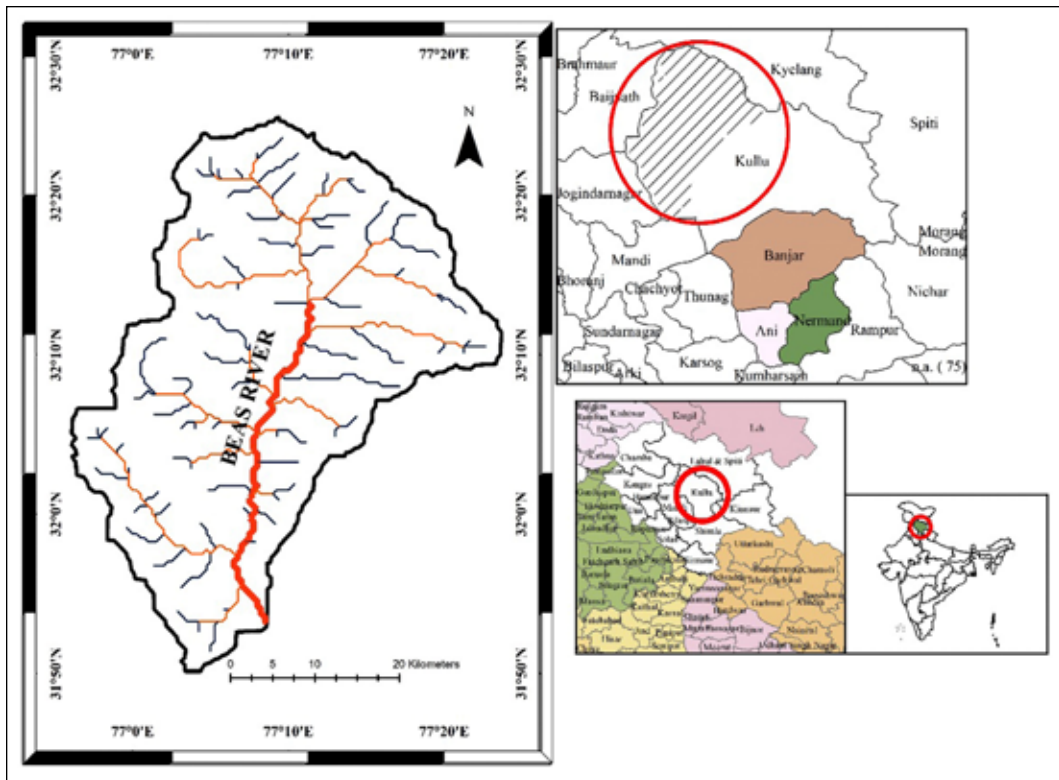


Fig. 1: Location and Drainage Network of the Upper Beas Basin, Himachal Pradesh, India

Source: Survey of India, 2011, Retrieved on 25th June 2025, Compiled and Prepared by Author

MATERIAL AND METHODS

Data Collection and Seasonal Classification

Temperature and precipitation data for 1981–2024 were obtained from NASA POWER (NASA POWER Project, n.d.). The supplied dataset contains 44 annual observations for each of four seasons: winter (December–February), pre-monsoon (March–May), monsoon (June–September), and post-monsoon (October–November). The analysis uses one seasonal series for each variable; it does not resolve spatial variation within the basin.

Calculation of Mean and Standard Deviation

The mean and standard deviation were calculated separately for each seasonal temperature and precipitation series using Microsoft Excel 2016. The mean represented the average seasonal conditions over the study period, while the standard deviation measured interannual variability around the corresponding mean.

Mean:
$$\mu = \frac{1}{n} \sum_{i=1}^n X_i$$

Where:

μ = Mean

X_i = Observed Value in year

n = Total Number of observations

For Standard Deviation:
$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \mu)^2}$$

Where:

σ = Standard Deviation

μ = Mean

X_i = Observed Value in year

n = Total Number of observations

Calculation of Standardised Climatic Indices:

- Standardised Precipitation Index (SPI)
- Standardised Temperature Index (STI)

Seasonal temperature and precipitation series were standardised using z-scores to assess climatic anomalies and interannual variability. Each score expressed the deviation of an observed seasonal value from its long-term seasonal mean in standard-deviation units:

$$Z = \frac{X - \mu}{\sigma}$$

Where:

Z = Standardised Index (SPI And STI)

X = Observed Seasonal Value

μ = Long-term mean of the Variable

σ = Standard Deviation of the Variable

This procedure placed temperature and precipitation on a common, dimensionless scale. Positive values indicated above-average conditions, whereas negative values indicated below-average conditions for the respective variable and season.

Principal Component Analysis

Principal Component Analysis (PCA) was conducted using IBM SPSS Statistics to reduce dimensionality and identify dominant patterns of covariability among the seasonal temperature and precipitation indices. The analysis involved the following steps:

Data preparation: The standardised seasonal series were checked to confirm that each had a mean of approximately zero and a standard deviation of approximately one.

Joint analysis of seasonal variables: PCA was applied to a single matrix comprising eight variables—the temperature and precipitation indices for each of the four seasons—with years representing observations.

Component extraction and retention: Components were extracted using the correlation matrix. Components with eigenvalues greater than one were retained according to Kaiser’s criterion. Their individual and cumulative contributions to the total variance were examined.

Component rotation and interpretation: Varimax orthogonal rotation was applied to simplify the loading structure and facilitate interpretation. Rotation redistributed the explained variance among the retained components without changing their cumulative explained variance. The components were interpreted according to the magnitude and relative signs of the loadings of the seasonal variables.

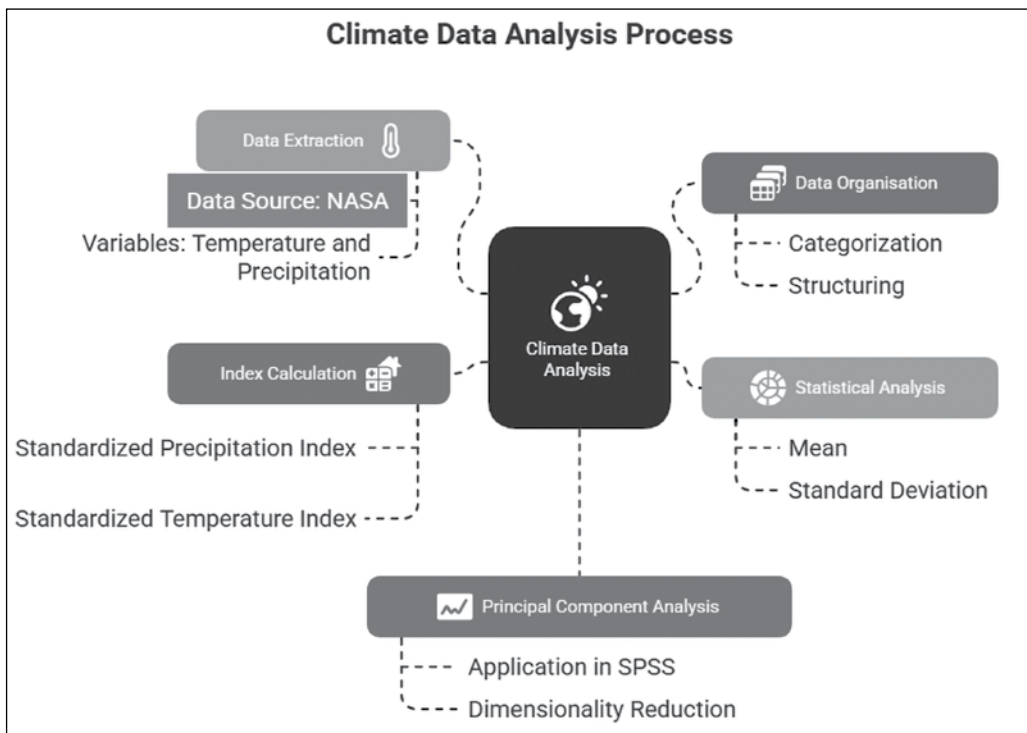


Fig. 2: Methodological Framework for Assessing Seasonal Climate Variability

Source: Prepared by Author

RESULTS AND DISCUSSION

Table 1: Seasonal Mean Precipitation in Kullu District, Himachal Pradesh

Year	Winter	Pre-Monsoon	Monsoon	Post-Monsoon
1981	1.10667	1.62333	5.155	1.145
1982	1.26667	4.59	1.8	0.175
1983	0.21333	0.52	1.6725	0.035
1984	0.32	0.37	3.0775	0.035
1985	0.67	0.58667	3.765	0.61
1986	0.34667	0.58333	1.4625	0.475
1987	0.60667	0.76333	1.475	0.465
1988	0.52333	0.39	3.3	0.025
1989	0.95333	0.39333	2.3275	0.21
1990	0.56333	0.95333	3.2	0.1
1991	0.18333	0.27667	2.7	0.02
1992	0.6	0.51	2.475	0.25
1993	0.50333	0.85	4.08	0.035
1994	0.69	0.54333	4.28	0.05
1995	0.98333	0.41333	4.085	0.1
1996	0.84667	0.65333	4.0075	0.41
1997	0.45	1.49667	3.405	0.63
1998	0.20333	0.58	3.12	1.005
1999	0.3	0.1	3.015	0.215
2000	0.56333	0.43	3.5425	0.025
2001	0.22333	0.83333	3.7425	0.05
2002	0.63	0.52	3.1725	0.075
2003	1.03667	0.47333	3.605	0.2
2004	0.64	0.65667	3.2025	0.44
2005	0.88	0.53333	3.4075	0.065
2006	0.37333	1.14	4.0025	0.42
2007	1.02667	0.85333	3.445	0.095
2008	0.39	1.02333	5.78	0.35
2009	0.43	0.72	2.7075	0.47
2010	0.56	0.28	6.035	0.22

Table 1 Contd....

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Year	Winter	Pre-Monsoon	Monsoon	Post-Monsoon
2011	0.43667	0.72333	5.1775	0.155
2012	0.53	0.48667	3.6	0.08
2013	1.44667	0.26667	6.2	0.42
2014	1.08667	1.01	3.635	0.275
2015	0.90667	1.32333	4.26	0.23
2016	0.65667	2.27333	2.8475	0.04
2017	2.31	1.98	3.095	0.145
2018	0.67333	1.18667	5.1	1.06
2019	2.68	1.19667	2.58	1.425
2020	1.24667	2.25333	3.045	1.24
2021	0.89	2.65	4.0075	0.86
2022	2.02667	0.69	5.14	1.185
2023	1.31333	3.30333	4.18	0.58
2024	1.67667	2.83667	3.7175	0

Source: NASA Power

Table 1 presents rainfall data for Kullu district, showing distinct seasonal patterns and interannual variability. Among the four seasons, the monsoon generally records the highest average rainfall, ranging from approximately 1.46 mm in 1986 to 6.20 mm in 2013. The concentration of rainfall between June and September highlights the importance of the summer monsoon to the study area. The particularly high value recorded in 2013 indicates a notably wet monsoon season, although identifying the underlying climatic drivers requires further analysis. Winter precipitation is generally lower than monsoon rainfall but exhibits considerable interannual variability. Relatively high values were recorded in 2017 (2.31 mm), 2019 (2.68 mm), and 2022 (2.03 mm), compared with lower values in 1991 (0.18 mm) and 1998 (0.20 mm). These differences demonstrate substantial variation in winter precipitation across the study period. Further investigation would be needed to determine whether these fluctuations are associated with changes in the frequency or intensity of western disturbances.

Pre-monsoon precipitation also varies considerably between years. Notable peaks occurred in 1982 (4.59 mm), 2016 (2.27 mm), and 2023 (3.30 mm). These values indicate wetter pre-monsoon conditions in the respective years, although seasonal averages do not reveal whether the additional precipitation resulted from more frequent rainfall events, greater event intensity, or longer duration. Several relatively high values in recent years warrant closer examination of possible changes in pre-monsoon precipitation patterns.

Post-monsoon precipitation is generally the lowest among the four seasons, although relatively wet years interrupt this pattern. Higher values were recorded in 2018 (1.06 mm), 2019 (1.43 mm), and 2020 (1.24 mm). These observations highlight occasional increases in post-monsoon precipitation. Their possible relationship with monsoon withdrawal or other atmospheric processes requires additional evidence.

Overall, the records highlight the predominance of monsoon rainfall alongside substantial interannual variation in the other seasons. Relatively high winter and pre-monsoon precipitation values in several recent years suggest the need for further investigation into seasonal changes and their potential implications for regional water resource planning.

Table 2: Seasonal Mean Temperature (°C) in Kullu District, Himachal Pradesh

Year	Winter	Pre-Monsoon	Monsoon	Post-Monsoon
1981	-18.97	-8.95	1.4175	-13.09
1982	-17.92	-10.703	0.6	-9.42
1983	-17.113	-9.05	2.0025	-9.1
1984	-17.863	-6.99	2.735	-10.39
1985	-17.973	-7.2867	2.0275	-10.35
1986	-17.91	-8.8733	1.96	-9.655
1987	-16.543	-8.6733	1.5825	-9.1
1988	-14.9	-7.7133	2.4125	-9.35
1989	-19.047	-9.3367	0.8925	-9.24
1990	-16.407	-9.7667	2.87	-9.07
1991	-16.013	-7.7833	2.1025	-10.05
1992	-16.803	-9.51	1.69	-8.58
1993	-15.88	-9.3933	1.2375	-8.495
1994	-17.157	-8.4767	2.59	-9.265
1995	-18.453	-9.6533	1.88	-8.87
1996	-17.123	-8.9133	2.11	-9.78
1997	-18.467	-9.4567	1.9725	-10.155
1998	-16.243	-7.9767	2.565	-9.185
1999	-15.573	-7.1067	2.225	-9.35
2000	-17.627	-7.6367	2.0875	-8.115
2001	-16.683	-7.1767	2.1875	-8.02
2002	-16.68	-7.5	1.405	-8.505
2003	-16.953	-9.18	2.195	-9.89

Table 2 Contd....

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Year	Winter	Pre-Monsoon	Monsoon	Post-Monsoon
2004	-16.95	-6.8033	1.79	-10.115
2005	-17.59	-9.3267	2.08	-10.03
2006	-15	-7.85	2.2475	-8.805
2007	-17.417	-8	2.565	-9.41
2008	-17.857	-7.7233	2.3875	-8.615
2009	-16.033	-8.2667	1.1875	-9.69
2010	-16.283	-5.8233	1.78	-8.15
2011	-18.22	-7.89	2.3325	-7.88
2012	-18.173	-8.7767	2.3375	-9.545
2013	-17.333	-8.0833	2.7425	-8.3
2014	-17.323	-9.3633	2.015	-8.38
2015	-16.24	-7.9133	1.9775	-7.425
2016	-15.593	-7.34	2.99	-7.29
2017	-16.773	-8.29	2.54	-7.86
2018	-18	-8.27	2.4775	-11.03
2019	-19.243	-9.2033	2.11	-10.165
2020	-19.473	-9.79	2.1225	-9.77
2021	-18.087	-9.7833	2.635	-9.87
2022	-18.183	-6.42	2.7475	-9.95
2023	-16.333	-10.23	2.4975	-8.6
2024	-17.27	-9.08	3.02	-6.1

Source: Prepared by Author

Table 2 presents seasonal mean temperatures for Kullu district. Winter temperatures (December–February) remained below zero throughout the study period, generally ranging from approximately -19°C to -15°C . Some of the coldest winters occurred in 2020 (-19.47°C) and 2019 (-19.24°C), whereas relatively warmer winters were recorded in 2006 (-15.00°C) and 1999 (-15.57°C). These fluctuations highlight considerable interannual variability. Individual warmer years, however, do not establish a long-term warming trend or identify its underlying causes.

Pre-monsoon temperatures (March–May) also exhibited interannual variability, generally ranging from approximately -10°C to -6°C . Relatively warm conditions were recorded in 2010 (-5.82°C) and 2022 (-6.42°C). Although these observations indicate occasional warmer pre-monsoon seasons, a sustained warming trend would need to be confirmed

through statistical analysis. Changes in pre-monsoon temperatures may have implications for snowmelt timing, spring agriculture, and seasonal water availability, although these effects were not directly assessed in the present study. Monsoon temperatures (June–September) were the highest among the four seasons, ranging from 0.60°C to 3.02°C. The highest seasonal mean was recorded in 2024 (3.02°C), followed by 2016 (2.99°C). Several relatively warm monsoon seasons occurred during the later years of the record, suggesting a possible warming tendency that warrants formal trend analysis. Determining the contribution of cloud cover, humidity, or broader regional climatic changes would require additional data.

Post-monsoon temperatures (October–November) also showed substantial interannual variation, with seasonal means generally falling between –10°C and –8°C. The warmest post-monsoon season occurred in 2024 (–6.10°C), while the lowest mean temperature was recorded in 1981 (–13.09°C). The post-monsoon season of 2018 was also relatively cold (–11.03°C). These contrasts show considerable variation during the transition to winter, although seasonal means alone cannot determine the influence of snowfall and radiational cooling. Overall, the temperature records reveal distinct seasonal differences and considerable interannual variability. Relatively warm monsoon conditions in several recent years merit further investigation, while the other seasons show a mixture of warmer and colder episodes. These patterns provide a basis for examining potential implications for snowpack dynamics, glacial melt, agricultural calendars, and mountain ecosystems in the Western Himalayas.

Table 3: Seasonal Standardised Precipitation and Temperature Indices in Kullu District, Himachal Pradesh

Year	SPI (Winter)	SPI (Pre-Monsoon)	SPI (Monsoon)	SPI (Post-Monsoon)	STI (Winter)	STI (Pre-Monsoon)	STI (Monsoon)	STI (Post-Monsoon)
1981	0.53253	0.64109	1.4267	2.04677	-1.6143	-0.4807	-1.3344	-3.4758
1982	0.82703	3.9117	-1.6172	-0.5012	-0.6457	-2.1315	-2.8846	-0.2117
1983	-1.1118	-0.5753	-1.7329	-0.8689	0.09839	-0.5749	-0.225	0.07287
1984	-0.9154	-0.7406	-0.4582	-0.8689	-0.5934	1.3646	1.16411	-1.0744
1985	-0.2712	-0.5018	0.16558	0.64146	-0.6949	1.08529	-0.1776	-1.0389
1986	-0.8664	-0.5055	-1.9234	0.28685	-0.6365	-0.4086	-0.3056	-0.4207
1987	-0.3878	-0.307	-1.9121	0.26059	0.62419	-0.2203	-1.0215	0.07287
1988	-0.5412	-0.7186	-0.2563	-0.8952	2.14009	0.68358	0.55253	-0.1495
1989	0.2503	-0.7149	-1.1386	-0.4092	-1.685	-0.8448	-2.3299	-0.0516
1990	-0.4675	-0.0976	-0.347	-0.6982	0.75026	-1.2496	1.42012	0.09955
1991	-1.167	-0.8435	-0.8007	-0.9083	1.11309	0.61768	-0.0353	-0.772
1992	-0.4001	-0.5863	-1.0048	-0.3042	0.38435	-1.008	-0.8176	0.53535

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Year	SPI (Winter)	SPI (Pre-Monsoon)	SPI (Monsoon)	SPI (Post-Monsoon)	STI (Winter)	STI (Pre-Monsoon)	STI (Monsoon)	STI (Post-Monsoon)
1993	-0.578	-0.2115	0.45137	-0.8689	1.23609	-0.8981	-1.6757	0.61095
1994	-0.2344	-0.5496	0.63283	-0.8295	0.05842	-0.0351	0.88914	-0.0739
1995	0.30552	-0.6929	0.45591	-0.6982	-1.1377	-1.1429	-0.4573	0.27743
1996	0.05396	-0.4283	0.38559	0.11611	0.08917	-0.4462	-0.0211	-0.5319
1997	-0.6762	0.50145	-0.161	0.694	-1.15	-0.9578	-0.2819	-0.8654
1998	-1.1302	-0.5091	-0.4196	1.67903	0.90093	0.43566	0.84173	-0.0027
1999	-0.9522	-1.0383	-0.5149	-0.3961	1.51897	1.25475	0.19696	-0.1495
2000	-0.4675	-0.6745	-0.0363	-0.8952	-0.3751	0.75576	-0.0638	0.94891
2001	-1.0934	-0.2298	0.14516	-0.8295	0.49505	1.18885	0.12585	1.03341
2002	-0.3448	-0.5753	-0.372	-0.7638	0.49812	0.88443	-1.3581	0.60205
2003	0.40368	-0.6267	0.02041	-0.4355	0.24599	-0.6973	0.14007	-0.6297
2004	-0.3264	-0.4246	-0.3448	0.19492	0.24906	1.54034	-0.628	-0.8299
2005	0.11532	-0.5606	-0.1588	-0.7901	-0.3413	-0.8354	-0.078	-0.7543
2006	-0.8173	0.10824	0.38106	0.14238	2.04784	0.55491	0.23963	0.33524
2007	0.38528	-0.2078	-0.1248	-0.7113	-0.1814	0.41369	0.84173	-0.2028
2008	-0.7866	-0.0204	1.99375	-0.0415	-0.5873	0.67417	0.50512	0.50422
2009	-0.713	-0.3548	-0.7939	0.27372	1.09464	0.16262	-1.7705	-0.4519
2010	-0.4737	-0.8399	2.2251	-0.383	0.86403	2.46301	-0.6469	0.91778
2011	-0.7007	-0.3511	1.44711	-0.5537	-0.9225	0.51725	0.40082	1.15792
2012	-0.5289	-0.612	0.01588	-0.7507	-0.8794	-0.3175	0.4103	-0.3229
2013	1.15834	-0.8546	2.37481	0.14238	-0.1045	0.33523	1.17833	0.78438
2014	0.49572	-0.0351	0.04763	-0.2385	-0.0953	-0.8699	-0.2013	0.71323
2015	0.1644	0.31036	0.61468	-0.3567	0.904	0.49528	-0.2724	1.56259
2016	-0.2958	1.35769	-0.6669	-0.8558	1.50052	1.03507	1.64768	1.68266
2017	2.74742	1.0343	-0.4423	-0.58	0.41203	0.14065	0.79432	1.17571
2018	-0.2651	0.15969	1.3768	1.8235	-0.7195	0.15948	0.6758	-1.6436
2019	3.42846	0.17071	-0.9095	2.78226	-1.8664	-0.7192	-0.0211	-0.8743
2020	0.79022	1.33564	-0.4877	2.29631	-2.0786	-1.2716	0.00259	-0.523
2021	0.13372	1.77294	0.38559	1.29815	-0.7995	-1.2653	0.97447	-0.612
2022	2.22591	-0.3879	1.41309	2.15184	-0.8886	1.90125	1.18781	-0.6831
2023	0.91293	2.49321	0.5421	0.56266	0.81791	-1.6858	0.71372	0.51756
2024	1.58169	1.97873	0.12248	-0.9609	-0.0461	-0.6031	1.70457	2.74102

Source: Prepared by Author

Table 3 shows considerable interannual variability in winter precipitation indices, with negative anomalies in 1991 (−1.17) and 1998 (−1.13), and pronounced positive anomalies in 2019 (3.43) and 2017 (2.75). These values indicate contrasting drier-than-average and wetter-than-average winters. Winter temperature indices also exhibit both negative and positive anomalies. Particularly cold conditions relative to the seasonal mean occurred in 2020 (−2.08) and 2019 (−1.87), whereas relatively warm conditions were recorded in 2006 and 1988. Together, these observations highlight substantial variation in winter precipitation and temperature, although their relationship with western disturbances, snow cover, or atmospheric circulation requires further investigation.

Pre-monsoon precipitation indices frequently show negative anomalies during the earlier decades, indicating below-average precipitation. Several years after 2015 exhibit positive anomalies, including 2021 (1.77) and 2023 (2.49), suggesting relatively wet pre-monsoon conditions during these years. The temperature indices display a contrasting pattern, with pronounced warm anomalies in 2010 (2.46) and 2022 (1.90), and a marked cold anomaly in 2023 (−1.69). These observations demonstrate considerable interannual variability in pre-monsoon conditions.

Further analysis would be needed to establish sustained trends or links with convective activity, snowmelt timing, and land-surface processes. Monsoon precipitation indices show pronounced positive anomalies in 2013 (2.37) and 2010 (2.23), alongside substantial negative anomalies in 1986 (−1.92) and 1987 (−1.91). These contrasts highlight considerable variation between wetter-than-average and drier-than-average monsoon seasons. Monsoon temperature indices show several positive anomalies in the later years of the record, including 2024 (1.70) and 2016 (1.65). This pattern suggests a possible warming tendency, although formal trend analysis is required to establish its magnitude and statistical significance. The potential implications for evapotranspiration, glacier dynamics, and agricultural water requirements also warrant further study.

Post-monsoon precipitation indices are negative in many years, indicating below-average precipitation relative to the post-monsoon reference mean. However, pronounced positive anomalies occurred in 2019 (2.78), 2020 (2.30), and 2022 (2.15), indicating notably wetter conditions. These seasonal values alone cannot establish whether the anomalies reflect delayed monsoon withdrawal or changes in rainfall frequency. Post-monsoon temperature indices also show contrasting conditions, ranging from a pronounced cold anomaly in 1981 (−3.48) to a strong warm anomaly in 2024 (2.74). These observations highlight substantial thermal variability during the transition to winter, with potential relevance to late-autumn agriculture and seasonal snow formation.

PCA DIAGNOSTICS AND VARIANCE EXPLAINED

The reported KMO value was 0.584, indicating modest sampling adequacy. Bartlett's test was significant, $\chi^2(28) = 83.782$, $p < 0.001$. Reconstruction from the rounded index table gave KMO = 0.583745 and $\chi^2 = 83.781$, consistent with the reported statistics at the available precision. These diagnostics support an exploratory reduction of the correlation structure, but do not establish component stability. Serial dependence among annual observations can also affect the inferential interpretation of Bartlett's test.

Table 4: Communalities of Seasonal Climate Indices in the Three-Component PCA Solution

Variable	Initial	Extraction
SPI_Winter	1	0.692
SPI_PreMon	1	0.723
SPI_Monsoon	1	0.63
SPI_PostMon	1	0.741
STI_Winter	1	0.631
STI_PreMon	1	0.726
STI_Monsoon	1	0.614
STI_PostMon	1	0.811

Source: Prepared by Author

Table 4 shows that the extraction communalities for all eight climatic variables exceeded 0.60, indicating that the three retained components collectively explained more than 60% of the variance in each variable. STI_PostMon had the highest communality (0.811), followed by SPI_PostMon (0.741), STI_PreMon (0.726), and SPI_PreMon (0.723). These values indicate that the retained components represented the seasonal indices reasonably well, particularly post-monsoon temperature, for which 81.1% of the variance was explained.

Table 5: Total Variance Explained by the Retained Components
Before and After Varimax Rotation

Component	Initial Eigenvalue	% of Variance	Cumulative %	Rotation SS Loadings	% of Variance (Rotated)
1	2.414	30.18%	30.18%	2.047	25.58%
2	1.653	20.66%	50.84%	1.881	23.52%
3	1.504	18.80%	69.63%	1.642	20.53%

Source: Prepared by Author

Table 5 presents three principal components with eigenvalues greater than one, collectively explaining 69.63% of the total variance in the eight climatic variables. Before rotation, Components 1, 2, and 3 accounted for 30.18%, 20.66%, and 18.80% of the variance, respectively. Following Varimax rotation, the explained variance was distributed more evenly across the components, with corresponding contributions of 25.58%, 23.52%, and 20.53%. Rotation facilitated interpretation while preserving the cumulative explained variance. The three components were retained according to Kaiser's criterion and provided a compact representation of the dominant patterns of seasonal climatic covariability.

Table 6: Varimax-Rotated Component Loadings of Seasonal Climate Indices

Variable	Component 1 (Temperature Impact)	Component 2 (Dry Season Precipitation)	Component 3 (Monsoon Heat)
SPI_Winter	-0.294	0.718	0.302
SPI_PreMon	0.032	0.844	-0.099
SPI_Monsoon	-0.165	-0.1	0.77
SPI_PostMon	-0.813	0.211	0.187
STI_Winter	0.73	-0.309	0.041
STI_PreMon	0.134	-0.653	0.531
STI_Monsoon	0.182	0.088	0.757
STI_PostMon	0.828	0.264	0.237

Source: Prepared by Author

Table 6 presents three components describing distinct patterns of seasonal climatic covariability. Component 1 shows strong positive loadings on STI_PostMon (0.828) and STI_Winter (0.730), alongside a strong negative loading on SPI_PostMon (-0.813). This component represents a pattern of warmer post-monsoon and winter conditions associated with lower post-monsoon precipitation. Component 2 is characterised by strong positive loadings on SPI_PreMon (0.844) and SPI_Winter (0.718), together with a negative loading on STI_PreMon (-0.653). It therefore captures a pattern of higher winter and pre-monsoon precipitation associated with cooler pre-monsoon conditions. Component 3 shows strong positive loadings on SPI_Monsoon (0.770) and STI_Monsoon (0.757), with a moderate positive loading on STI_PreMon (0.531). This component represents covariability between monsoon precipitation and temperature, with an additional contribution from pre-monsoon temperature. Together, the rotated components summarise the principal associations among seasonal temperature and precipitation anomalies in the study area.

Table 7: Interpretation of Rotated Components of Seasonal Climate Variability in Kullu District

Component	Dominant Loadings	Interpretation Summary
PC1	STI_Winter, STI_PostMon	Seasonal Temperature Variability (Cooler to Warmer Shift)
PC2	SPI_PreMon, SPI_Winter	Dry Season Precipitation Trends
PC3	SPI_Monsoon, STI_Monsoon, STI_PreMon	Monsoon Intensity and Associated Warming

Source: Prepared by Author

Table 7 summarises the interpretation of three rotated components describing seasonal climate variability in Kullu district, Himachal Pradesh, during 1981–2024. Each component captures a distinct pattern of association among seasonal temperature and precipitation indices. The first component (PC1) is characterised by a strong negative loading on SPI_PostMon (−0.813) and strong positive loadings on STI_PostMon (+0.828) and STI_Winter (+0.730). It therefore represents a post-monsoon dryness–temperature pattern, with its positive direction corresponding to drier post-monsoon conditions alongside warmer post-monsoon and winter temperatures. These associations may provide a basis for further investigation of cold-season moisture and thermal conditions.

The second component (PC2) shows strong positive loadings on SPI_PreMon (+0.844) and SPI_Winter (+0.718), together with a negative loading on STI_PreMon (−0.653). It represents non-monsoon precipitation variability, linking wetter winter and pre-monsoon conditions with cooler pre-monsoon temperatures. This pattern offers a basis for examining potential implications for early-season water availability and agricultural activities, although the role of western disturbances requires independent evidence. The third component (PC3) combines positive loadings on SPI_Monsoon (+0.770), STI_Monsoon (+0.757), and STI_PreMon (+0.531). It captures a pattern of monsoon precipitation–temperature covariability, with warmer pre-monsoon and monsoon conditions associated with wetter monsoon conditions along this component. These loadings describe seasonal associations; they do not establish changes in heatwave occurrence, monsoon onset, or break spells.

Together, the three components provide a concise interpretation of seasonal climatic covariability in the study area. They can help guide further investigation of climate-sensitive water resources and agricultural systems, contributing to the evidence base for adaptation planning in mountain regions.

CONCLUSION

This study examined long-term seasonal climate variability in the Upper Beas Basin using precipitation and temperature data for 1981–2024. Standardised seasonal indices were analysed through principal component analysis (PCA) to identify dominant patterns of

climatic covariability across winter, pre-monsoon, monsoon, and post-monsoon seasons. The findings reveal distinct seasonal differences and considerable interannual variability in both precipitation and temperature. Precipitation exhibited pronounced seasonality, with the monsoon generally recording the highest seasonal mean values, while winter and pre-monsoon precipitation showed substantial interannual variation. Temperature patterns also differed across seasons, with considerable variability in winter, pre-monsoon, monsoon, and post-monsoon conditions. Several recent monsoon seasons were comparatively warm, and a pronounced warm anomaly was observed during the post-monsoon season in 2024. However, these observations should be interpreted cautiously, as formal trend analysis is required to establish the magnitude and statistical significance of long-term climatic changes.

The principal contribution of the study is the joint analysis of seasonal temperature and precipitation indices using PCA. Three retained components explained 69.63% of the total variance, summarising the dominant patterns within the eight climatic variables. The first component (PC1) captured warmer post-monsoon and winter conditions associated with lower post-monsoon precipitation. The second component (PC2) represented non-monsoon precipitation variability, combining higher winter and pre-monsoon precipitation with cooler pre-monsoon temperatures. The third component (PC3) captured monsoon precipitation–temperature covariability, linking wetter monsoon conditions with warmer monsoon and pre-monsoon temperatures. Together, these components demonstrate that seasonal climate variability in the Upper Beas Basin involves several distinct patterns of association between temperature and precipitation. The findings highlight the value of considering these variables jointly rather than examining them in isolation. However, the statistical patterns identified through PCA should not be interpreted as direct evidence of physical mechanisms, climatic attribution, or increasing hydroclimatic risk.

The findings provide a useful basis for further research and for incorporating seasonal climate information into discussions of water resource management, agricultural planning, and climate adaptation in mountain regions. Future research should strengthen the analysis through formal trend assessment, spatial comparisons, hydrological modelling, and the integration of vulnerability indicators. With appropriate validation, the analytical framework may also be applied to other mountain basins to contribute to a broader understanding of seasonal climate variability in the Western Himalayas.

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