

## Article

# Regional Variability and Spatio-Temporal Dynamics of Groundwater Quality in the Western Himalayas: An Integrated WQI and Hydrochemical Assessment

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## Abstract

Groundwater is an essential freshwater resource in the Western Himalayas, where increasing anthropogenic pressure and environmental variability are raising concerns regarding groundwater quality and water security. However, regionally integrated assessments of groundwater-quality variability across the Western Himalayan states remain limited. This study evaluates groundwater quality across Jammu and Kashmir, Himachal Pradesh, and Uttarakhand using groundwater-monitoring data obtained from the Central Ground Water Board (CGWB). A total of 338 observation wells monitored during 2019–2022 were analyzed using the weighted arithmetic Water Quality Index (WQI) based on Bureau of Indian Standards (BIS) and World Health Organization (WHO) drinking-water guidelines. Spatial and temporal variability were examined through hydrochemical, correlation, and geospatial analyses. The results reveal substantial regional and district-level variability in groundwater quality across the Western Himalayas. Groundwater in Himachal Pradesh and Uttarakhand is predominantly classified as excellent to good, whereas Jammu and Kashmir exhibit greater hydrochemical heterogeneity and localized groundwater deterioration. Elevated WQI values are concentrated within foothill and valley-transition districts, while high-altitude recharge zones generally maintain lower WQI values. Hydrochemical analyses indicate that groundwater-quality variability is primarily associated with mineralization processes, lithological controls, and localized anthropogenic influences. Temporal analysis further indicates moderate groundwater-quality improvement between 2019 and 2022, particularly in parts of Jammu and Kashmir. Overall, the findings demonstrate that groundwater systems across the Western Himalayas remain largely controlled by hydrogeological conditions but are increasingly modified by localized anthropogenic pressures. Strengthened groundwater monitoring, protection of recharge zones, and targeted management of vulnerable foothill and valley-transition environments will be essential for sustaining long-term water security in this climate-sensitive mountain region.



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**Keywords:** anthropogenic influence; groundwater quality assessment; hydrochemical variability; Water Quality Index; Western Himalayas; water security

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## 1. Introduction

Groundwater is an essential freshwater resource for drinking, domestic use, and irrigation in mountain environments, where surface-water availability is often seasonally constrained, and settlements frequently depend on local springs and shallow aquifers [1,2]. In the Himalayas, this dependence is particularly pronounced because steep terrain, dispersed habitations, and limited storage infrastructure increase reliance on groundwater as a relatively accessible and reliable source. However, the long-standing assumption that mountain groundwater systems remain naturally protected is becoming increasingly uncertain under rapid population growth, tourism expansion, agricultural intensification, land-use transformation, and climate-driven hydrological variability [3–5]. Consequently, groundwater quality has emerged as a major concern for water security, ecosystem integrity, and human health in environmentally fragile mountain regions [6–9].

The Western Himalayas present a particularly sensitive hydrogeological setting because groundwater occurrence and chemistry are controlled by strong topographic gradients, fractured lithology, active tectonics, and highly variable recharge regimes [10,11]. Rock–water interaction, mineral dissolution, and weathering of carbonate and silicate formations define much of the regional hydrochemical background [12]. However, these natural controls are increasingly modified by anthropogenic influences arising from sewage leakage, unregulated waste disposal, fertilizer use, expanding road networks, and land-use change in valleys and foothill settlements [9,13,14]. Consequently, regional land-use patterns provide important context for understanding spatial variations in groundwater quality across the Western Himalayan region. The interaction between lithological controls and anthropogenic pressures therefore produces substantial spatial heterogeneity in groundwater chemistry, making single-parameter evaluation insufficient for regional-scale assessment and management-oriented interpretation [15–18].

Water Quality Index (WQI) approaches, particularly the Weighted Arithmetic Water Quality Index, are widely used for groundwater-quality assessment because they integrate multiple physicochemical parameters into a single and interpretable measure of water suitability [19–26]. Previous studies conducted across different parts of the Himalayan region have provided valuable insights into local groundwater conditions and generally report acceptable groundwater quality, while also identifying localized deterioration associated with mineralization processes, urban expansion, agricultural activity, and foothill transition zones [27–32]. However, most of these investigations have been restricted to individual watersheds, valleys, districts, or localized aquifer systems and therefore provide limited understanding of groundwater-quality variability at broader regional scales. Furthermore, many studies primarily focus on WQI-based classification and descriptive hydrochemical assessment, with limited attention to the combined evaluation of temporal variability, spatial clustering patterns, and hydrochemical relationships within a unified analytical framework. As a result, important questions concerning the regional-scale distribution of groundwater-quality conditions, spatial heterogeneity, and the interaction between hydrogeological controls and anthropogenic pressures across the Western Himalayan region remain insufficiently understood.

Groundwater-quality management in the Western Himalayas requires an understanding of how hydrogeological conditions, recharge processes, lithological controls, and anthropogenic pressures interact across diverse mountain environments. Such understand-

ing is difficult to obtain from localized case studies alone because groundwater-quality responses often vary considerably between high-altitude recharge zones, intermontane valleys, foothill environments, and rapidly urbanizing districts. A regionally integrated assessment is therefore necessary for distinguishing relatively resilient groundwater systems from areas experiencing increasing hydrochemical stress and supporting evidence-based groundwater management. The integrated methodological framework adopted in this study is particularly suited to the Western Himalayas because it combines WQI assessment with hydrochemical evaluation, temporal analysis, and Local Indicators of Spatial Association (LISA). While WQI provides a standardized measure of groundwater suitability, hydrochemical analyses help identify dominant geogenic and anthropogenic controls, temporal evaluation reveals inter-annual variability, and LISA analysis enables identification of localized clustering and groundwater-quality hotspots. By integrating these complementary approaches within a single regional framework, this study advances beyond most previous Himalayan groundwater assessments that have focused primarily on localized WQI evaluation or site-specific hydrochemical characterization.

Against this background, the present study undertakes a comparative spatio-temporal assessment of groundwater quality across Jammu and Kashmir, Himachal Pradesh, and Uttarakhand using Central Ground Water Board (CGWB) monitoring data and the weighted arithmetic Water Quality Index (WQI) method. By integrating groundwater-quality assessment with hydrochemical, temporal, and spatial analyses, this study provides a comprehensive evaluation of groundwater-quality variability and its controlling factors across the Western Himalayas.

Specifically, this study aims to (i) evaluate groundwater suitability for drinking purposes; (ii) compare regional and district-level groundwater-quality patterns; (iii) examine temporal variation during 2019–2022; and (iv) interpret dominant hydrochemical associations using distributional, correlation-based, multivariate, and spatial analytical approaches. We hypothesize that groundwater quality across the Western Himalayas exhibits pronounced spatial variability, with relatively favorable conditions in high-altitude recharge environments and increasing hydrochemical deterioration within foothill and valley-transition districts subject to greater anthropogenic pressure.

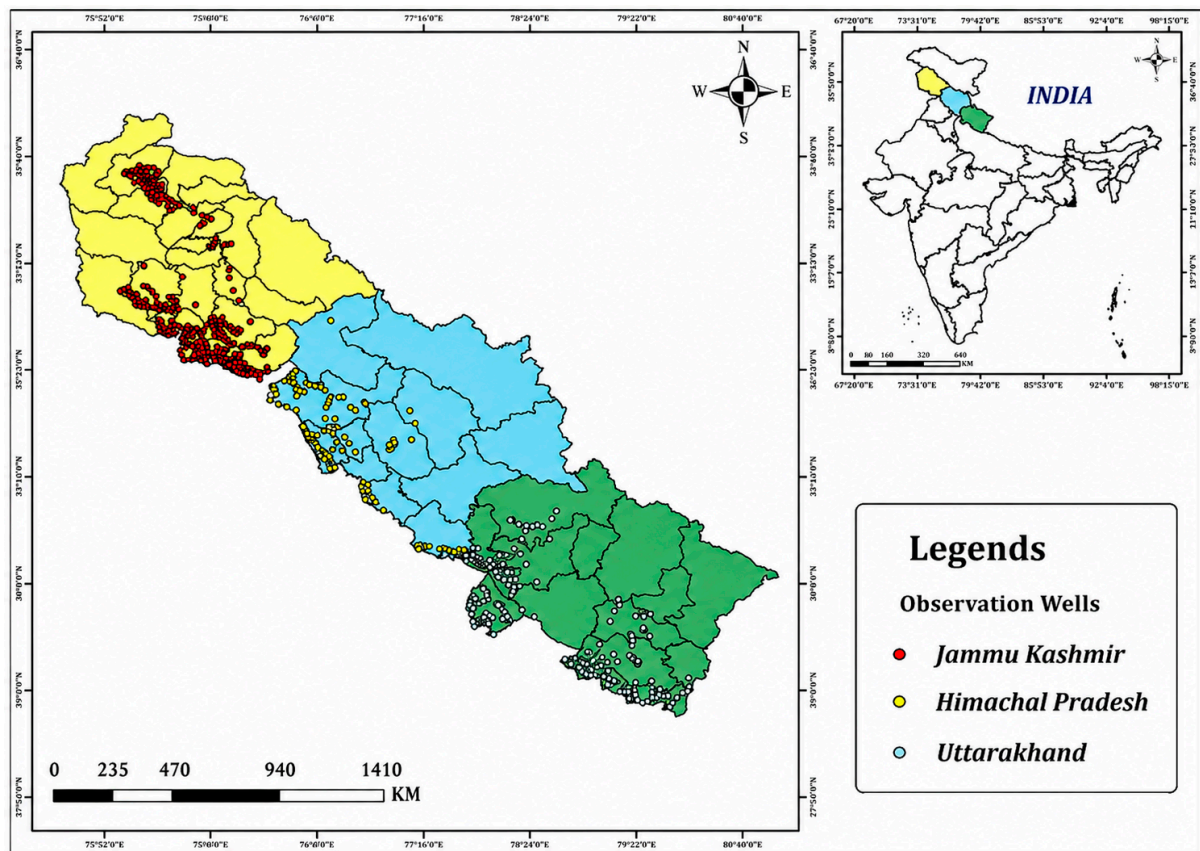
## 2. Materials and Methods

### 2.1. Study Area

The present study covers the Western Himalayan region of India, encompassing the states of Jammu and Kashmir (Union Territory of Jammu and Kashmir, including the Kashmir Valley and Jammu region), Himachal Pradesh, and Uttarakhand. Geographically, the region extends approximately from 73°52' E to 80°40' E longitude and 30° N to 37° N latitude, forming a significant segment of the Indian Himalayan arc. As shown in Figure 1, Jammu and Kashmir are represented in yellow, Himachal Pradesh in blue, and Uttarakhand in green. The study area spans a pronounced altitudinal gradient extending from the Greater Himalayas to the Siwalik foothills. The terrain is predominantly mountainous and characterized by steep slopes, deep river valleys, rugged topography, and active tectonic features associated with the ongoing Indian–Eurasian plate collision. Major river systems, including the Indus, Chenab, Ravi, Beas, Sutlej, and Ganga and their tributaries, drain the region and contribute to regional hydrological connectivity and groundwater recharge.

The Western Himalayas exhibit substantial climatic variability associated with altitude and seasonality, ranging from subtropical conditions in foothill regions to temperate and alpine environments at higher elevations. Precipitation is influenced by both the southwest monsoon and western disturbances, resulting in marked spatial and temporal variability in

water availability. Snowfall and glacial melt at higher elevations additionally contribute to streamflow maintenance and groundwater recharge.



**Figure 1.** Location map of investigated study area.

Hydrogeologically, the region comprises diverse geological formations, including alluvial deposits, Siwalik sediments, carbonate sequences, metamorphic rocks, granites, gneisses, schists, quartzites, and other crystalline formations associated with the Lesser and Greater Himalayas [10–12]. Groundwater occurs within both porous alluvial aquifers and fractured-rock aquifer systems. In the Kashmir Basin and Tarai–Bhabar plains, groundwater is mainly stored within unconsolidated alluvial deposits exhibiting relatively high storage capacity and transmissivity. In contrast, groundwater in mountainous terrains is predominantly stored and transmitted through fractures, joints, faults, weathered zones, and other forms of secondary porosity within crystalline and metamorphic rocks [10–12]. Springs constitute an important manifestation of groundwater discharge and serve as a major source of water supply for many rural settlements across the region.

Recharge occurs through multiple pathways, including rainfall infiltration, snowmelt, river seepage, subsurface flow from upland recharge areas, and localized recharge through colluvial and alluvial deposits [10–12]. Consequently, groundwater occurrence and availability exhibit substantial spatial variability across the Western Himalayan region.

Land-use and land-cover (LULC) patterns across the Western Himalayan region are highly heterogeneous and provide important environmental context for interpreting groundwater-quality variability (see Supplementary Figure S1). Open forest constitutes the dominant land-cover class (33.36% of the study area), followed by agricultural land (22.15%), snow-covered areas (15.36%), barren land (10.82%), dense forest (7.52%), water bodies (7.43%), and built-up land (3.35%). Forest and snow-dominated landscapes are concentrated primarily in higher-elevation Himalayan zones, whereas agricultural and

built-up areas occur predominantly within foothill districts, river valleys, and urban centers. These spatial patterns are particularly relevant to groundwater systems because recharge processes, runoff generation, and potential contaminant inputs vary substantially among land-cover types. Agricultural and urbanized landscapes may increase groundwater vulnerability through fertilizer application, wastewater discharge, and land-use intensification, whereas forested and snow-dominated uplands generally support groundwater recharge and experience comparatively lower anthropogenic pressure.

Previous studies have generally reported acceptable groundwater quality across much of the Western Himalayas; however, localized deterioration has been documented in foothill districts, urbanized valleys, and agricultural regions [27–30,33,34]. Reported concerns include elevated dissolved solids, hardness, nitrate, and fluoride concentrations associated with both natural hydrogeochemical processes and anthropogenic activities [27–30,34].

This study utilizes groundwater observations from 338 monitoring wells distributed across the three states to assess regional groundwater characteristics and spatial variability. Figure 1 illustrates the spatial distribution of the monitoring network, with comparatively denser coverage in the Kashmir Valley, Himachal foothill districts, and the Tarai–Bhabar zone of Uttarakhand. The monitoring network captures a broad range of hydrogeological settings, including high-altitude recharge zones, intermontane valleys, foothill plains, and rapidly developing transition districts.

## 2.2. Dataset Description

Groundwater-quality data were obtained from the Central Ground Water Board (CGWB) for major physicochemical parameters used in Water Quality Index (WQI) estimation, including pH, electrical conductivity (EC), total dissolved solids (TDS), total hardness (TH), calcium ( $\text{Ca}^{2+}$ ), magnesium ( $\text{Mg}^{2+}$ ), chloride ( $\text{Cl}^-$ ), sulfate ( $\text{SO}_4^{2-}$ ), nitrate ( $\text{NO}_3^-$ ), and fluoride ( $\text{F}^-$ ). Additional hydrochemical variables, including bicarbonate ( $\text{HCO}_3^-$ ), carbonate ( $\text{CO}_3^{2-}$ ), sodium ( $\text{Na}^+$ ), potassium ( $\text{K}^+$ ), and selected trace constituents, were retained for supplementary hydrochemical interpretation and data-quality assessment. The compiled dataset comprised groundwater samples from 338 observation wells distributed across Uttarakhand (150 wells), Himachal Pradesh (80 wells), and Jammu and Kashmir (108 wells), thereby providing broad spatial representation across the principal hydrogeological settings of the Western Himalayas. The CGWB dataset identifies these locations as groundwater-monitoring observation wells; however, information regarding the specific end use of individual wells (e.g., domestic, agricultural, or other purposes) was not available in the published records. Descriptive statistics for the groundwater-quality parameters used in the WQI assessment are presented in Table 1.

**Table 1.** Descriptive statistics of groundwater-quality parameters across the Western Himalayan study region (2019–2022).

| Parameters/<br>Indices         | Max         |                  |                   | Min         |                  |                   | Mean        |                  |                   | SD          |                  |                   |
|--------------------------------|-------------|------------------|-------------------|-------------|------------------|-------------------|-------------|------------------|-------------------|-------------|------------------|-------------------|
|                                | Uttarakhand | Himachal Pradesh | Jammu and Kashmir | Uttarakhand | Himachal Pradesh | Jammu and Kashmir | Uttarakhand | Himachal Pradesh | Jammu and Kashmir | Uttarakhand | Himachal Pradesh | Jammu and Kashmir |
| pH                             | 9.2         | 9.1              | 9.99              | 6.91        | 7.1              | 6.15              | 7.76        | 8.1              | 7.78              | 0.29        | 0.33             | 0.62              |
| EC ( $\mu\text{S}/\text{cm}$ ) | 2091        | 1145             | 2100              | 65          | 142              | 70                | 458.29      | 431.5            | 492.5             | 249.27      | 214.02           | 295.15            |
| TDS (mg/L)                     | 1254.6      | 922              | 1344              | 39          | 82.55            | 42                | 274.97      | 262.24           | 333.39            | 149.56      | 119.72           | 180.01            |
| TH (mg/L)                      | 770         | 440              | 1010              | 20          | 30               | 22                | 201.07      | 152.52           | 265.76            | 105.15      | 59.58            | 119.59            |
| $\text{Ca}^{2+}$ (mg/L)        | 152         | 120              | 250               | 2           | 6                | 4                 | 47.43       | 33.86            | 58.3              | 23.88       | 15.84            | 38.07             |
| $\text{Mg}^{2+}$ (mg/L)        | 127         | 68               | 216               | 0           | 2                | 3                 | 19.95       | 16.63            | 28.72             | 15.68       | 10.26            | 20.67             |
| $\text{Cl}^-$ (mg/L)           | 362         | 248              | 354               | 3.5         | 6.7              | 0                 | 19.41       | 36.52            | 34.09             | 24.38       | 31.11            | 38.58             |
| $\text{SO}_4^{2-}$ (mg/L)      | 1410        | 167              | 290               | 0           | 0                | 0                 | 30.99       | 21.77            | 30.63             | 75.03       | 29.04            | 30.8              |
| $\text{NO}_3^-$ (mg/L)         | 119         | 155              | 421.67            | 0           | 0                | 0                 | 9.11        | 20.77            | 24.15             | 15.84       | 21.22            | 42.63             |
| $\text{F}^-$ (mg/L)            | 4.42        | 13               | 8.58              | 0           | 0.01             | 0                 | 0.18        | 0.2              | 0.37              | 0.33        | 0.71             | 0.42              |

Note: Source: Authors' computation based on CGWB groundwater-quality monitoring data (2019–2022).

### 2.3. Missing Data Treatment and Imputation

Groundwater-quality datasets frequently contain incomplete observations because of irregular monitoring frequency, analytical limitations, and inconsistencies in laboratory reporting. Prior to hydrochemical analysis, the compiled datasets for Uttarakhand, Himachal Pradesh, and Jammu and Kashmir were screened for missing values, duplicate entries, and inconsistent observations. Parameter-wise missingness was evaluated to assess the extent and distribution of incomplete records across the hydrochemical variables.

To minimize information loss while preserving the multivariate hydrochemical structure of the datasets, a two-stage imputation framework was implemented. All random seeds were fixed (random state = 42) to ensure reproducibility of the imputation workflow. In the first stage, provisional missing values were estimated using an Iterative Imputer with an ExtraTreesRegressor as the base estimator. In the second stage, parameter-specific Random Forest (RF) regression models were developed for variables containing missing observations, using the remaining hydrochemical variables as predictors. The RF approach was selected because of its ability to capture nonlinear hydrochemical relationships while remaining robust to outliers and collinearity among predictor variables.

To reduce spatial leakage and overoptimistic performance estimates, model validation was conducted using district-blocked GroupKFold cross-validation ( $K = 5$ ), ensuring that samples from the same district were not simultaneously included in both training and validation subsets. Imputation performance was evaluated using out-of-fold predictions and standard validation metrics, including the coefficient of determination ( $R^2$ ), mean absolute error (MAE), and root mean squared error (RMSE). Any residual missing observations remaining after RF prediction were replaced using parameter-specific median values.

The imputation framework demonstrated satisfactory predictive performance for major hydrochemical parameters exhibiting strong inter-parameter relationships, whereas sparsely distributed trace constituents showed comparatively lower predictive reliability. Parameters exhibiting unstable predictive performance were excluded from Water Quality Index (WQI) estimation where appropriate. Parameter-wise missingness distributions for Uttarakhand, Himachal Pradesh, and Jammu and Kashmir are provided in Supplementary Figures S2–S4.

### 2.4. Water Quality Index (WQI) Methodology

The Water Quality Index (WQI) framework adopted in this study follows the weighted arithmetic index approach and was used to synthesize multiple physicochemical parameters into a single interpretable measure of groundwater suitability for drinking purposes.

#### 2.4.1. Parameters and Standards

The WQI was calculated using the weighted arithmetic method in accordance with the Bureau of Indian Standards (BIS IS 10500:2012) [34] and WHO (2021) guidelines [35]. The selected physicochemical parameters (pH, EC, TDS, TH,  $\text{Ca}^{2+}$ ,  $\text{Mg}^{2+}$ ,  $\text{Cl}^-$ ,  $\text{SO}_4^{2-}$ ,  $\text{NO}_3^-$ , and  $\text{F}^-$ ) were chosen based on their relevance to drinking-water quality assessment, the availability of established guideline values under BIS IS 10500:2012 and WHO recommendations, and their widespread use in groundwater-quality studies. Collectively, these parameters represent key groundwater characteristics, including salinity, mineralization, hardness, and potential contamination arising from both natural hydrogeochemical processes and anthropogenic activities. Parameter selection was further guided by data completeness and consistency across the CGWB monitoring network to ensure comparability among states and years. Variables lacking appropriate drinking-water standards or sufficient data coverage were excluded from WQI computation but retained for supplementary hydrochemical

interpretation and data-quality assessment. The standard and ideal values used for WQI estimation are presented in Table 2.

**Table 2.** Parameters and corresponding standard and ideal values used for WQI estimation.

| Parameter                      | Standard Limit ( $S_i$ ) | Ideal Value ( $I_i$ ) | Unit                    | Source            |
|--------------------------------|--------------------------|-----------------------|-------------------------|-------------------|
| pH                             | 8.5                      | 7                     | –                       | BIS IS 10500:2012 |
| Electrical conductivity (EC)   | –                        | –                     | $\mu\text{S}/\text{cm}$ | –                 |
| Total dissolved solids (TDS)   | 500                      | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Total hardness (TH)            | 200                      | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Calcium ( $\text{Ca}^{2+}$ )   | 75                       | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Magnesium ( $\text{Mg}^{2+}$ ) | 30                       | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Chloride ( $\text{Cl}^{-}$ )   | 250                      | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Sulfate ( $\text{SO}_4^{2-}$ ) | 200                      | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Nitrate ( $\text{NO}_3^{-}$ )  | 45                       | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |
| Fluoride ( $\text{F}^{-}$ )    | 1                        | 0                     | $\text{mg L}^{-1}$      | BIS IS 10500:2012 |

Note: Other available hydrochemical variables (e.g.,  $\text{Na}^+$ ,  $\text{K}^+$ ,  $\text{HCO}_3^-$ ,  $\text{CO}_3^{2-}$ ,  $\text{SiO}_2$ , and  $\text{PO}_4^{3-}$ ) were retained for supplementary hydrochemical interpretation and data-quality assessment but were not directly incorporated into the WQI computation. For electrical conductivity (EC), no direct BIS drinking-water standard is specified; therefore, EC was included as an indicator of groundwater mineralization and salinity in the WQI assessment.

#### 2.4.2. Mathematical Formulation

For  $n$  measured parameters, the WQI is calculated as the weighted mean of sub-indices ( $q_i$ ) using corresponding unit weights ( $W_i$ ). To maintain statistical robustness, only samples containing at least five valid parameters were assigned a WQI value.

The overall WQI is calculated using the following formula:

$$WQI = \frac{\sum_{i=1}^n W_i q_i}{\sum_{i=1}^n W_i} \quad (1)$$

The unit weight ( $W_i$ ) for each parameter is inversely proportional to its standard limit:

$$W_i = \frac{K}{S_i} \quad (2)$$

where  $K$  is the proportionality constant, calculated as follows:

$$K = \frac{1}{\sum_{i=1}^n \frac{1}{S_i}} \quad (3)$$

The quality rating ( $q_i$ ), or sub-index, for each parameter is given by the following:

$$q_i = \left( \frac{C_i}{S_i} \right) \times 100 \quad (4)$$

where  $C_i$  is the observed concentration of the parameter.

For pH, which has an ideal value and an acceptable range, the quality rating ( $q_{pH}$ ) was calculated based on its deviation from the ideal value of 7.0:

$$q_{pH} = \left( \frac{C_{pH} - I_{pH}}{S_{pH} - I_{pH}} \right) \times 100 \quad (5)$$

where  $C_{pH}$  is the observed pH,  $I_{pH}$  is the ideal value (7.0), and  $S_{pH}$  is the standard limit (8.5).

### 2.4.3. Classification Criteria

The computed WQI values were classified into five qualitative groundwater-quality categories following the conventional weighted arithmetic classification framework proposed by Brown et al. [9], as shown in Table 3.

**Table 3.** Water quality classification standards used in this study.

| Range  | Water Quality Class | Description                           |
|--------|---------------------|---------------------------------------|
| ≤25    | Excellent           | Suitable for drinking                 |
| 25–50  | Good                | Minor treatment required              |
| 50–75  | Poor                | Major treatment required              |
| 75–100 | Very poor           | Unsuitable without advanced treatment |
| >100   | Unsuitable          | Unsafe for human consumption          |

### 2.5. Statistical Analysis

Descriptive statistics and Pearson correlation analysis were employed to characterize groundwater-quality variability and examine relationships among hydrochemical parameters. Descriptive statistical analyses were conducted to summarize the central tendency, dispersion, and distribution of groundwater-quality parameters across the study region. Summary statistics, including minimum, maximum, mean, and standard deviation, were calculated separately for Jammu and Kashmir, Himachal Pradesh, and Uttarakhand. Pearson correlation analysis was performed using pairwise complete observations to evaluate linear relationships among hydrochemical variables and to identify the dominant controls on groundwater mineralization and groundwater-quality variability.

Temporal variability in groundwater quality was examined using annual median Water Quality Index (WQI) values for the period of 2019–2022. Median aggregation was adopted to reduce the influence of extreme observations and to facilitate interannual comparisons.

Data processing, missing-value imputation, WQI computation, statistical analyses, and spatial data handling were performed using Python 3.12.3 and associated scientific libraries, including Pandas 2.2.3, NumPy 2.2.0, Scikit-learn 1.6.1, GeoPandas 1.0.1, and PySAL 24.7. Geographic data processing, visualization, and map preparation were conducted using QGIS 3.40, while Local Indicators of Spatial Association (LISA) analyses were implemented using PySAL-based spatial statistical tools.

### 2.6. Data Aggregation, Visualization, and Interpretation

To facilitate consistent spatial analysis, district names were standardized using predefined normalization and alias-correction procedures. For spatial and temporal interpretation, median WQI values were calculated at both district and annual scales to reduce sensitivity to extreme observations and to evaluate interannual groundwater-quality variation. Spatial visualization and interpretation were based on district-level WQI aggregation, hydrochemical parameter distributions, correlation patterns, and Local Indicators of Spatial Association (LISA) results. The integrated interpretation framework was used to evaluate spatial heterogeneity, temporal variability, and localized groundwater-quality anomalies across the Western Himalayan region.

### 2.7. Spatial Analysis

This study employed a Local Indicators of Spatial Association (LISA) workflow to analyze groundwater chemistry observations from the Indian states of Uttarakhand, Himachal Pradesh, and Jammu and Kashmir. The dataset for each region contained geographic

coordinates; the sampling year; and measured concentrations for a suite of analytes, including nitrate (NO<sub>3</sub><sup>-</sup>), fluoride (F<sup>-</sup>), total dissolved solids (TDS), and calcium (Ca<sup>2+</sup>), among others. Before analysis, the data underwent a comprehensive pre-processing routine. This began with reprojecting the geographic coordinates from WGS84 (EPSG:4326) to an appropriate UTM zone (EPSG:326xx) to ensure that all distance-based calculations were accurate and meaningful. Following projection, a strict boundary clip was applied using the official state polygons to remove any data points outside the study areas. The analysis was conducted on a year-by-year basis for the period of 2019–2022, with the year treated as a discrete variable. Finally, an inclusion rule was enforced, requiring at least eight finite observations for any given analyte in a particular year to ensure the statistical stability of the spatial neighbor structures. Figure 2 shows the complete methodology framework for groundwater assessment across the Western Himalayas.

The spatial relationships between sampling locations were defined using a k-nearest neighbor (KNN) weights matrix, with *k* set to 8, which was subsequently row-standardized. This standardization process enforces that the sum of weights for each location’s neighborhood equals one, guaranteeing comparable influence across all sites despite irregular sampling densities.

$$\sum_j w_{ij} = 1 \tag{6}$$

To identify local spatial patterns, the Local Moran’s I statistic was computed. This involved first standardizing the observed value of an analyte at each site, *i* (*x<sub>i</sub>*), by subtracting the mean ( $\bar{x}$ ) and dividing by the standard deviation (*s*). The standardized value (*z<sub>i</sub>*) and its spatial lag (*z<sub>i</sub><sup>(W)</sup>*) are defined as follows:

$$z_i = \frac{x_i - \bar{x}}{s}, z_i^{(W)} = \sum_j w_{ij}z_j \tag{7}$$

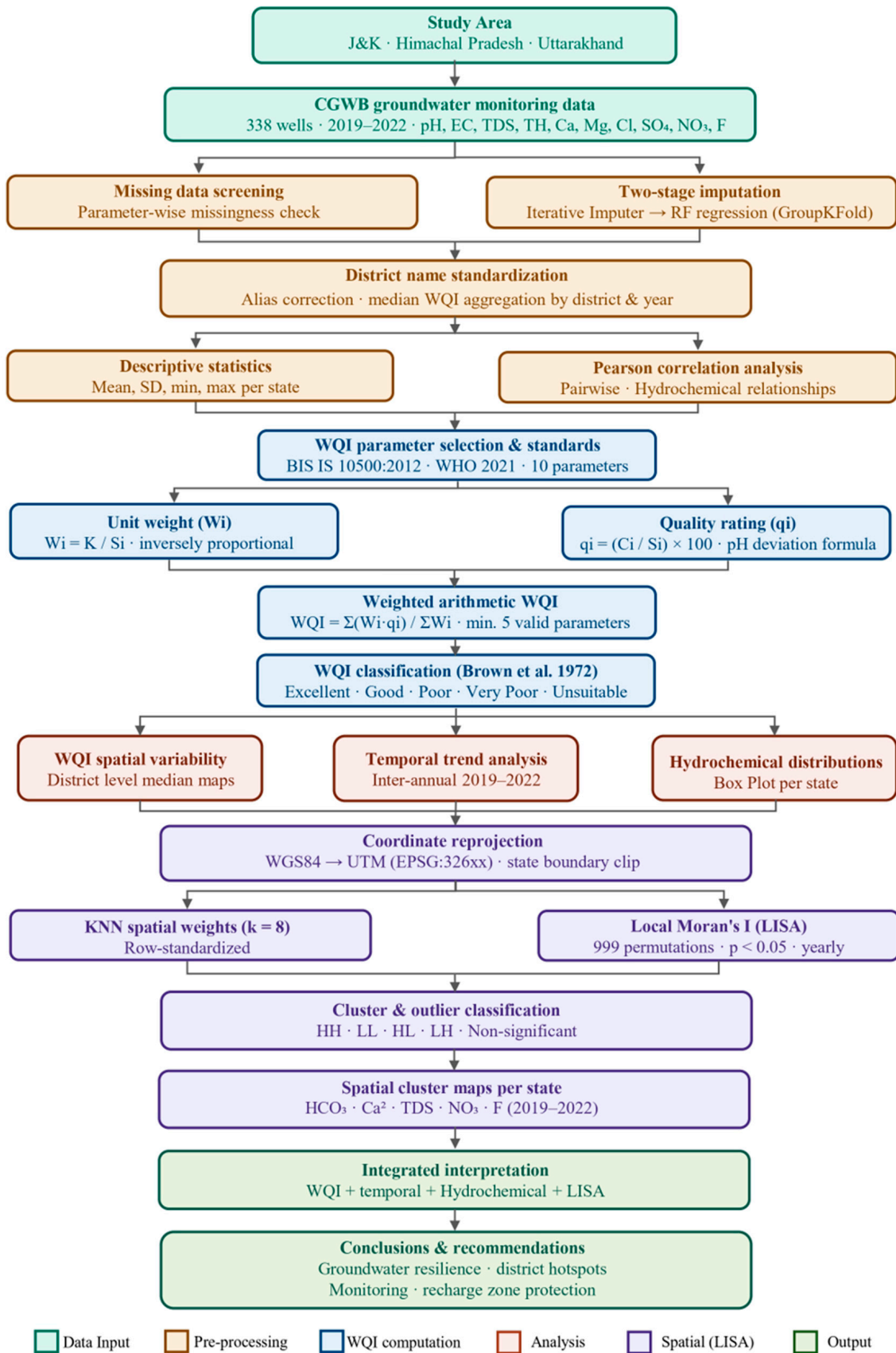
The Local Moran’s statistic at location (*i*) was calculated as follows:

$$p_i = \frac{\#\{I_i^{*(b)} \geq I_i^{obs}\} + 1}{B + 1} (B = 999) \tag{8}$$

Significant local patterns were classified into four cluster and outlier types based on the Moran scatterplot interpretation, which considers the signs of the standardized value (*z<sub>i</sub>*) and its spatial lag (*z<sub>i</sub><sup>(W)</sup>*). These types are High–High (HH), representing a cluster of high values; Low–Low (LL), a cluster of low values; High–Low (HL), an outlier where a high value is surrounded by low values; and Low–High (LH), an outlier where a low value is surrounded by high values. The statistical significance of these local patterns was assessed using a Monte-Carlo permutation test with 999 permutations. This procedure involves holding the spatial graph fixed while randomly shuffling the attribute values across locations to generate a reference distribution. The *p*-value for each location, *i*, was computed based on this distribution, with a threshold of *p* < 0.05 used to identify statistically significant clusters and outliers.

$$p_i = \frac{\#\{I_i^{*(b)} \geq I_i^{obs}\} + 1}{B + 1} (B = 999) \tag{9}$$

Locations that did not meet this significance threshold were labeled non-significant (NS).



**Figure 2.** Methodological framework for groundwater-quality assessment across the Western Himalayas. The Water Quality Index (WQI) classification is based on Brown et al. [36].

### 3. Results

The Water Quality Index (WQI) and associated hydrochemical analyses were used to evaluate groundwater quality across Uttarakhand, Himachal Pradesh, and Jammu and Kashmir. The results presented in this section describe the statistical distribution of WQI values, groundwater-quality classification patterns, district-level spatial variability, physicochemical parameter distributions, and inter-parameter correlation structures across the Western Himalayan region.

#### 3.1. Water Quality Index (WQI)

The distribution of Water Quality Index (WQI) values in Uttarakhand exhibits a strong right-skewed pattern, indicating that most groundwater samples fall within lower WQI ranges associated with better water quality (Figure 3A). A large proportion of observations are concentrated below WQI 50, corresponding to excellent-to-good quality conditions, whereas the extended tail towards higher WQI values reflects the occurrence of localized hotspots of degraded water quality, highlighting substantial spatial heterogeneity across the state.

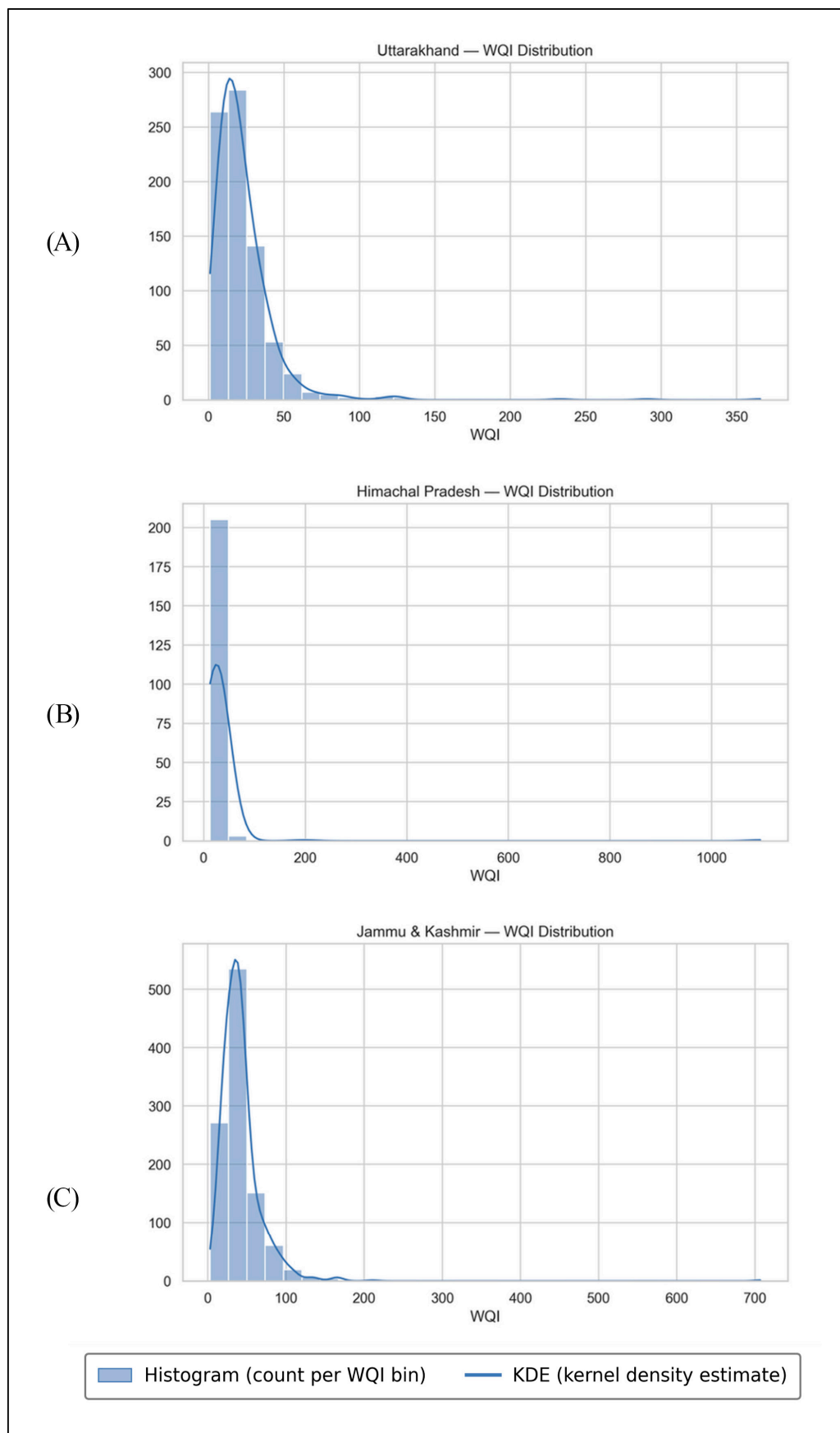
In Himachal Pradesh, the WQI distribution indicates that groundwater quality across the sampled districts is predominantly within safe and acceptable limits (Figure 3B). The overall WQI distribution is tightly concentrated in the lower range, largely between 15 and 40, reflecting generally favorable groundwater quality conditions. Although the distribution is positively skewed, the right tail is driven by a limited number of extreme observations, implying that pockets of deterioration are localized rather than representative of the broader hydrochemical regime of the state.

In Jammu and Kashmir, the WQI distribution reveals considerable variability in groundwater quality across the sampled districts (Figure 3C). The overall WQI distribution is positively skewed, with most values clustered between 20 and 80, while a long right tail extends beyond 200 and reaches nearly 700 in a few samples. This indicates that, although a large share of groundwater remains within acceptable limits, several localized settings experience pronounced hydrochemical deterioration. The extreme outliers point to site-specific contamination or intensified mineralization associated with anthropogenic pressure, geogenic controls, or inadequate waste-management practices.

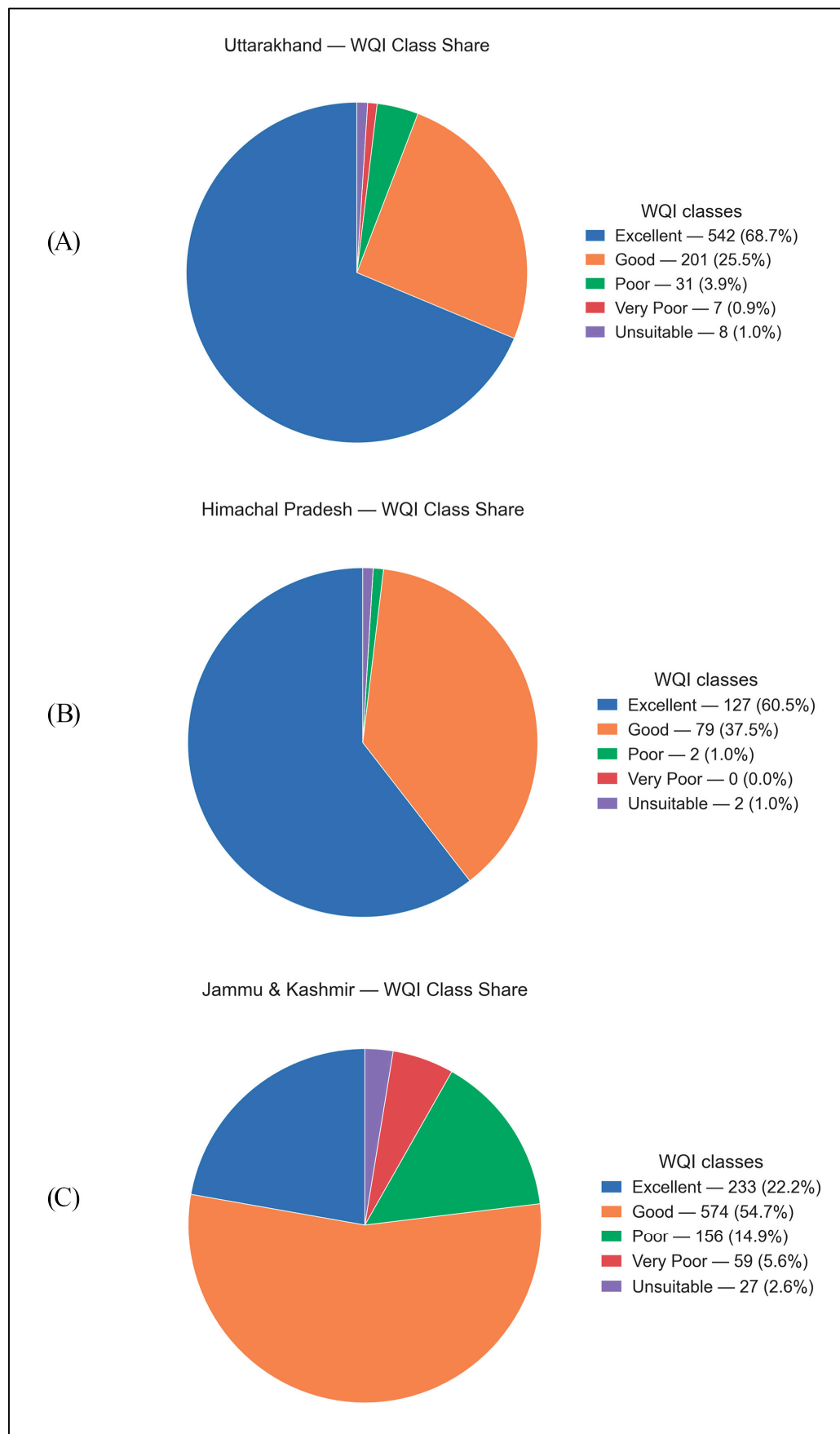
Across all three states, the predominance of lower WQI values indicates generally acceptable groundwater conditions in much of the Western Himalayan region. Nevertheless, the presence of long right tails and extreme outliers demonstrate localized zones of groundwater-quality deterioration, emphasizing the uneven spatial distribution of hydrochemical stress across the study area.

#### 3.2. Water Quality Classification

The classification of WQI values further confirms the predominance of good-quality groundwater resources in Uttarakhand (Figure 4A). Among the analyzed samples, 68.7% were categorized as “Excellent,” followed by 25.5% under the “Good” category. Together, these classes account for more than 94% of the total samples, indicating generally favorable groundwater quality conditions across the region. In contrast, the Poor (3.9%), Very Poor (0.9%), and Unsuitable (1.0%) categories constitute only a small fraction of the samples and are mainly associated with localized anthropogenic pressures such as urbanization, agricultural runoff, and industrial activities, particularly in the plains and peri-urban districts.



**Figure 3.** Distribution of groundwater Water Quality Index (WQI) values in (A) Uttarakhand, (B) Himachal Pradesh, and (C) Jammu and Kashmir (2019–2022).



**Figure 4.** Distribution of groundwater-quality classes based on Water Quality Index (WQI) in (A) Uttarakhand, (B) Himachal Pradesh, and (C) Jammu and Kashmir.

Similarly, in Himachal Pradesh, the categorical classification corroborates this pattern, with 60.5% of samples falling in the “Excellent” category and 37.6% in the “Good” category, together accounting for more than 98% of all samples (Figure 4B). Only 1.0% of samples were classified as “Poor” and another 1.0% as “Unsuitable for human consumption”, while no sample fell in the “Very Poor” class. These results indicate that groundwater in Himachal Pradesh is largely suitable for drinking, with only limited local areas requiring close surveillance or remedial intervention.

In Jammu and Kashmir, more than half of the samples (54.7%) fall under the “Good” category and 22.2% under the “Excellent” category. However, compared with Uttarakhand and Himachal Pradesh, Jammu and Kashmir show a substantially larger degraded fraction: 14.9% of samples are “Poor”, 5.6% are “Very Poor”, and 2.6% are “Unsuitable for human consumption” (Figure 4C). Collectively, nearly one-fourth of the samples indicate varying levels of groundwater stress, confirming that water-quality deterioration is not isolated to a few exceptional observations but is embedded across several districts.

### 3.3. Spatial Variability in WQI

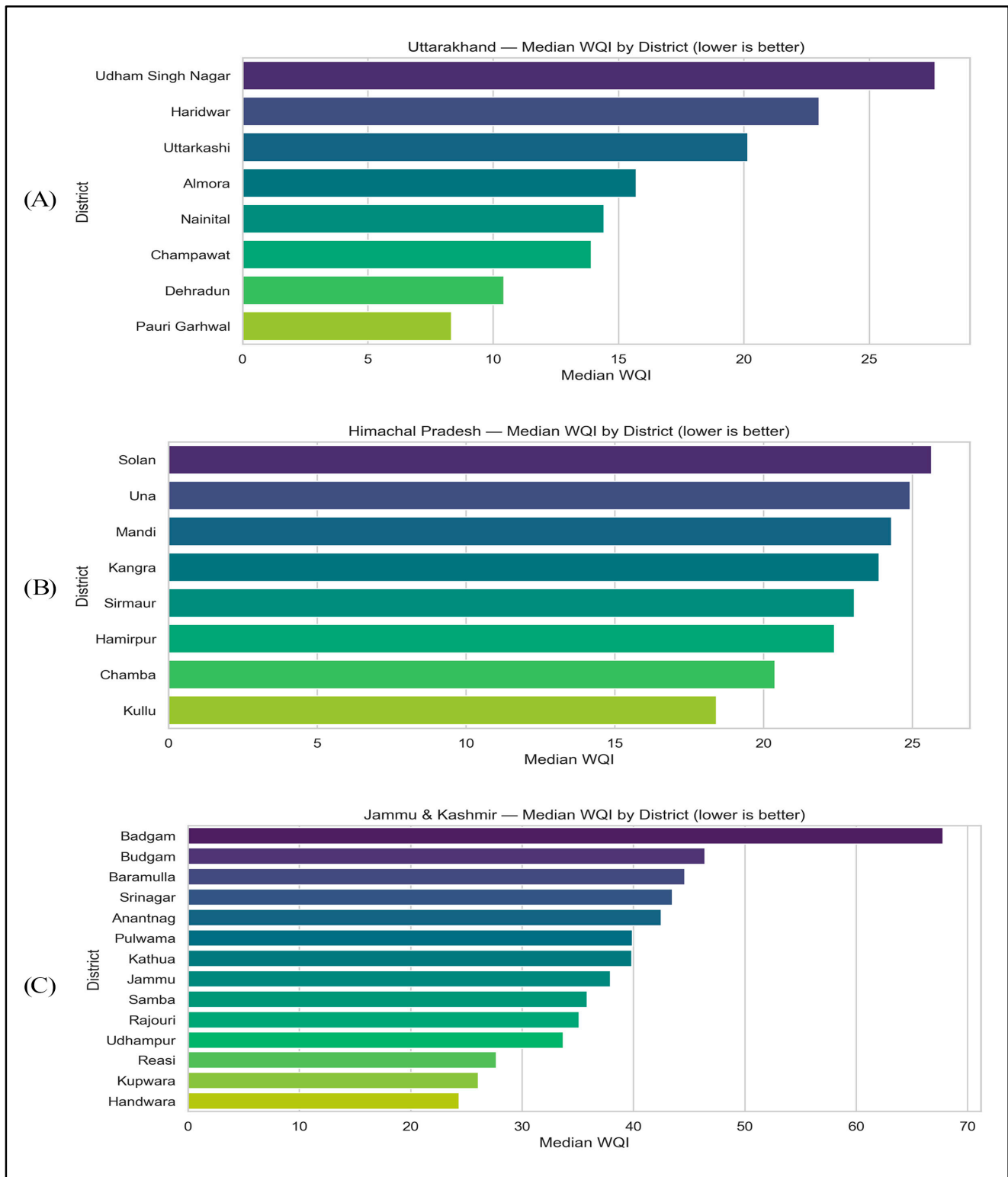
District-level analysis reveals pronounced spatial variability in WQI values across Uttarakhand (Figure 5A). Pauri Garhwal and Dehradun exhibit comparatively lower median WQI values, reflecting better groundwater quality conditions, likely supported by higher forest cover and lower industrial intensity. Conversely, Udham Singh Nagar and Haridwar show relatively higher median WQI values, indicating greater groundwater quality deterioration due to intensive agriculture, industrial clusters, and higher population density in the Tarai–Bhabar and downstream Ganga plains. Intermediate WQI levels were observed in districts such as Almora, Nainital, Champawat, and Uttarkashi, suggesting combined influences of natural lithological controls and anthropogenic activities.

In Himachal Pradesh, district-wise median WQI values reveal limited but discernible spatial variation (Figure 5B). Kullu records the lowest median WQI, indicating comparatively better groundwater quality, followed by Chamba and Hamirpur. In contrast, Solan and Una show relatively higher median WQI values, although these remain within the “Good” category. Such spatial differences most likely reflect variations in lithology, land use, settlement density, agricultural intensity, and localized industrial pressure along the foothill transition belt.

Similarly, district-wise median WQI values in Jammu and Kashmir demonstrate marked spatial heterogeneity (Figure 5C). Districts such as Handwara, Kupwara, and Reasi exhibit comparatively lower median WQI values, whereas Budgam, Srinagar, and parts of the Jammu plain show relatively elevated values, suggesting stronger urban or land-use influence. Intermediate values in Rajouri, Pulwama, Kathua, Jammu, and Samba indicate mixed hydrochemical conditions. These inter-district contrasts likely arise from differences in population concentration, wastewater loading, agricultural activity, valley confinement, and local hydrogeological settings.

### 3.4. Distribution of Physicochemical Parameters

The parameter-wise boxplots for Uttarakhand (Figure 6A) indicate that pH is comparatively stable, whereas EC,  $\text{HCO}_3^-$ , total hardness, and TDS show much broader interquartile ranges and numerous upper-end outliers. This distribution suggests that most groundwater samples are weakly to moderately mineralized, but a smaller set of observations from specific districts exhibits pronounced ionic enrichment. Chloride, sulfate, nitrate, sodium, and potassium remain comparatively lower in central tendency, although their scattered outliers indicate localized anthropogenic influence or mixed lithological control.



**Figure 5.** District-level median Water Quality Index (WQI) across (A) Uttarakhand, (B) Himachal Pradesh, and (C) Jammu and Kashmir (2019–2022).

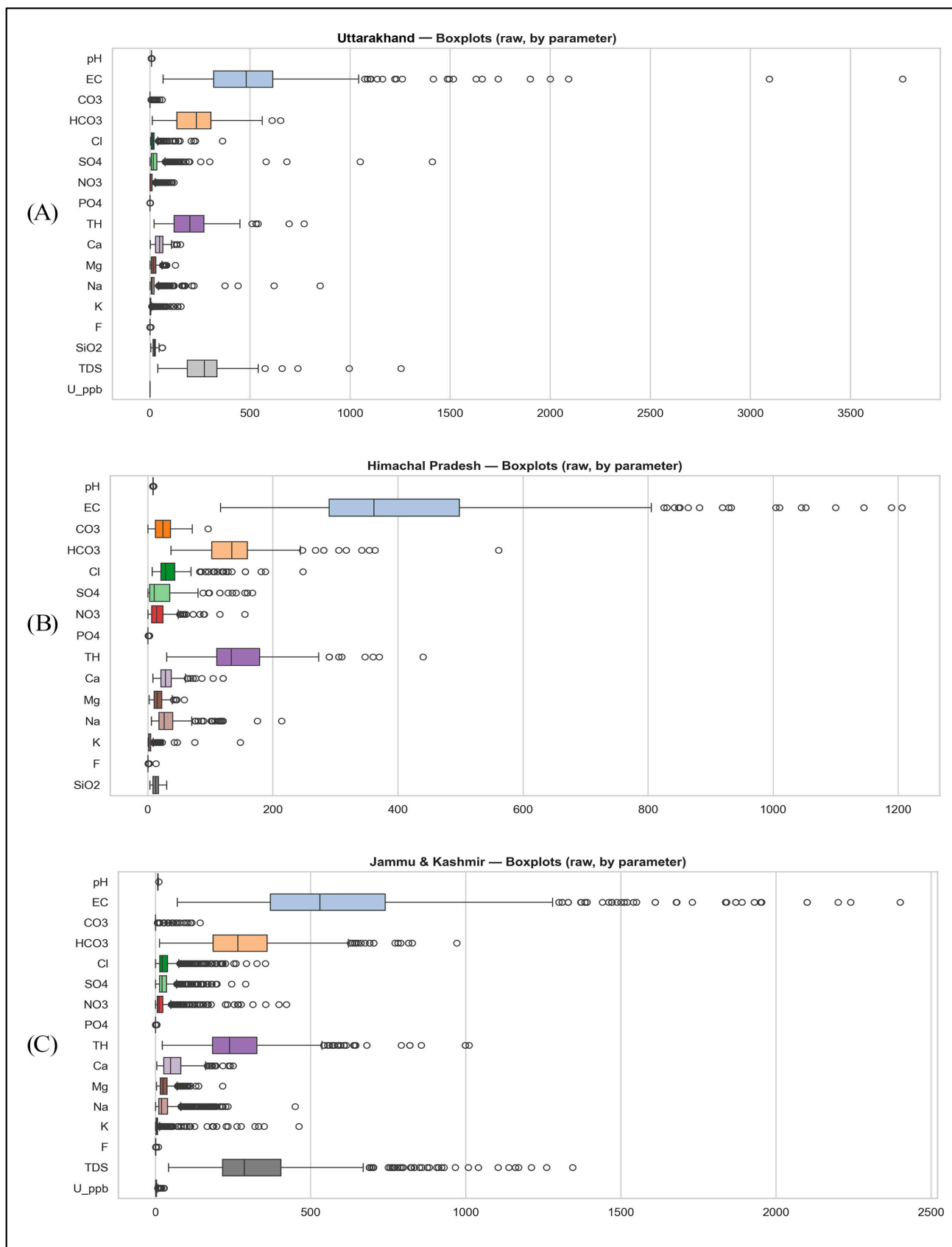


Figure 6. Boxplots showing the distribution of physicochemical groundwater parameters in (A) Uttarakhand, (B) Himachal Pradesh, and (C) Jammu and Kashmir.

Similarly, the boxplot analysis for Himachal Pradesh highlights considerable variability among groundwater-quality attributes across the study area (Figure 6B). Parameters such as TDS, hardness, chloride, and nitrate exhibit wider interquartile ranges and the presence of several outliers, indicating localized hydrochemical enrichment and anthropogenic influence in certain districts. In contrast, parameters such as pH remain relatively stable within permissible limits, suggesting overall geochemical stability of groundwater systems in Himachal Pradesh.

The boxplot analysis for Jammu and Kashmir demonstrates the widest parameter spread among the three study states (Figure 6C), with especially large dispersion and numerous upper-tail outliers in EC,  $\text{HCO}_3^-$ , total hardness, TDS, and several dissolved ions. This pattern confirms that the groundwater system contains both relatively fresh and strongly mineralized water types, and that extreme values are not restricted to a single constituent. Compared with Himachal Pradesh and Uttarakhand, nitrate and chloride also show more pronounced scattered outliers, suggesting stronger localized anthropogenic loading in some districts.

### 3.5. Correlation Structure of Groundwater Parameters

The Pearson correlation heatmap of Uttarakhand (Figure 7) further shows that EC and TDS are positively associated with hardness and the major dissolved ions, especially  $\text{Ca}^{2+}$ ,  $\text{Mg}^{2+}$ ,  $\text{HCO}_3^-$ ,  $\text{Cl}^-$ , and  $\text{SO}_4^{2-}$ , pointing to a common mineralization process as the principal driver of groundwater-quality variation. These relationships are consistent with the observed WQI distribution and indicate that groundwater chemistry is primarily controlled by dissolved mineral constituents.

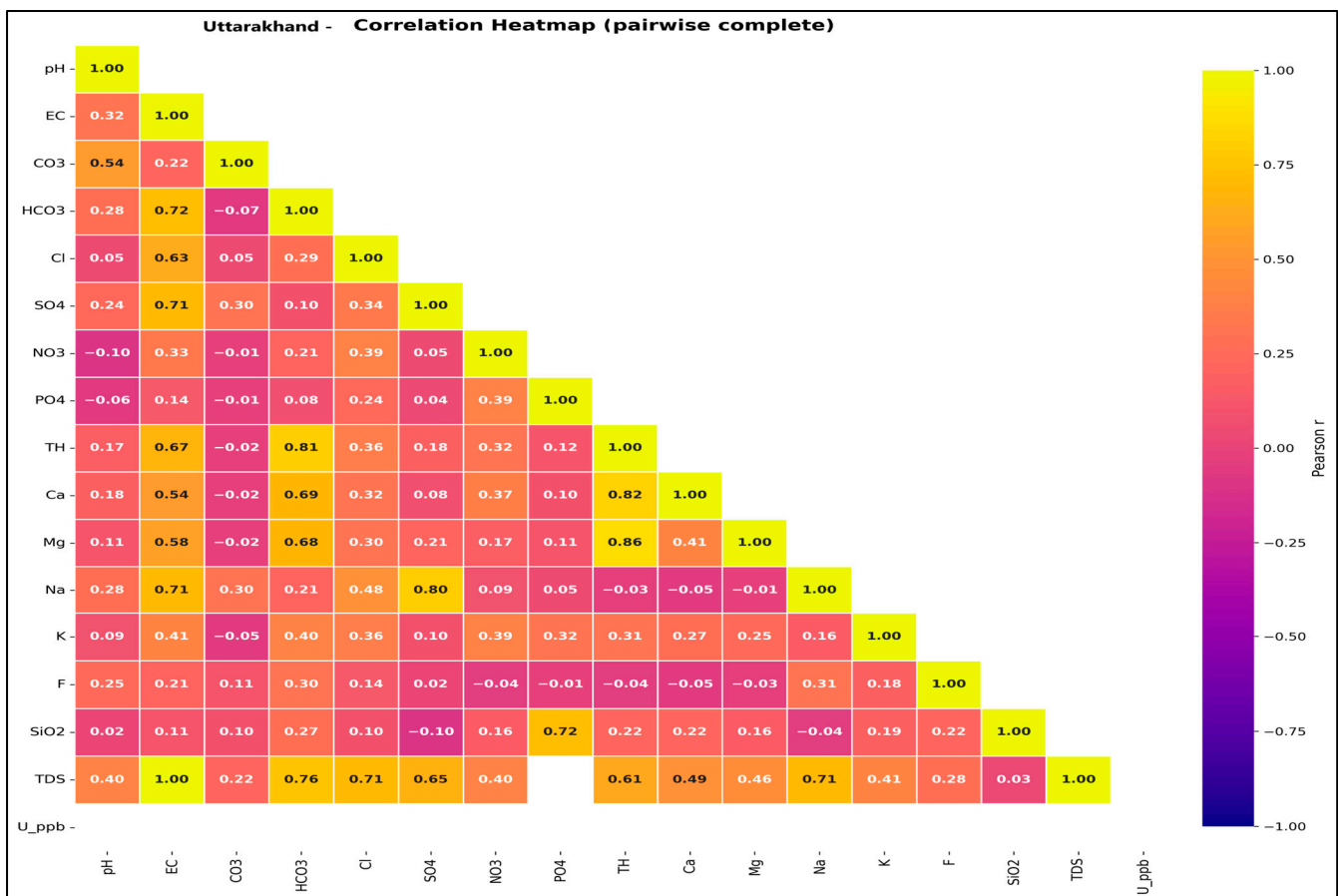


Figure 7. Pearson correlation matrix of physicochemical groundwater parameters in Uttarakhand.

Similarly, the Pearson correlation matrix for Himachal Pradesh provides insights into the interrelationships among groundwater-quality parameters (Figure 8). Strong positive correlations among EC, TDS, hardness, chloride, and sulfate indicate a common geogenic origin and mineral dissolution processes controlling groundwater chemistry. Moderate correlations between nitrate and other ionic constituents may reflect localized agricultural and anthropogenic inputs.

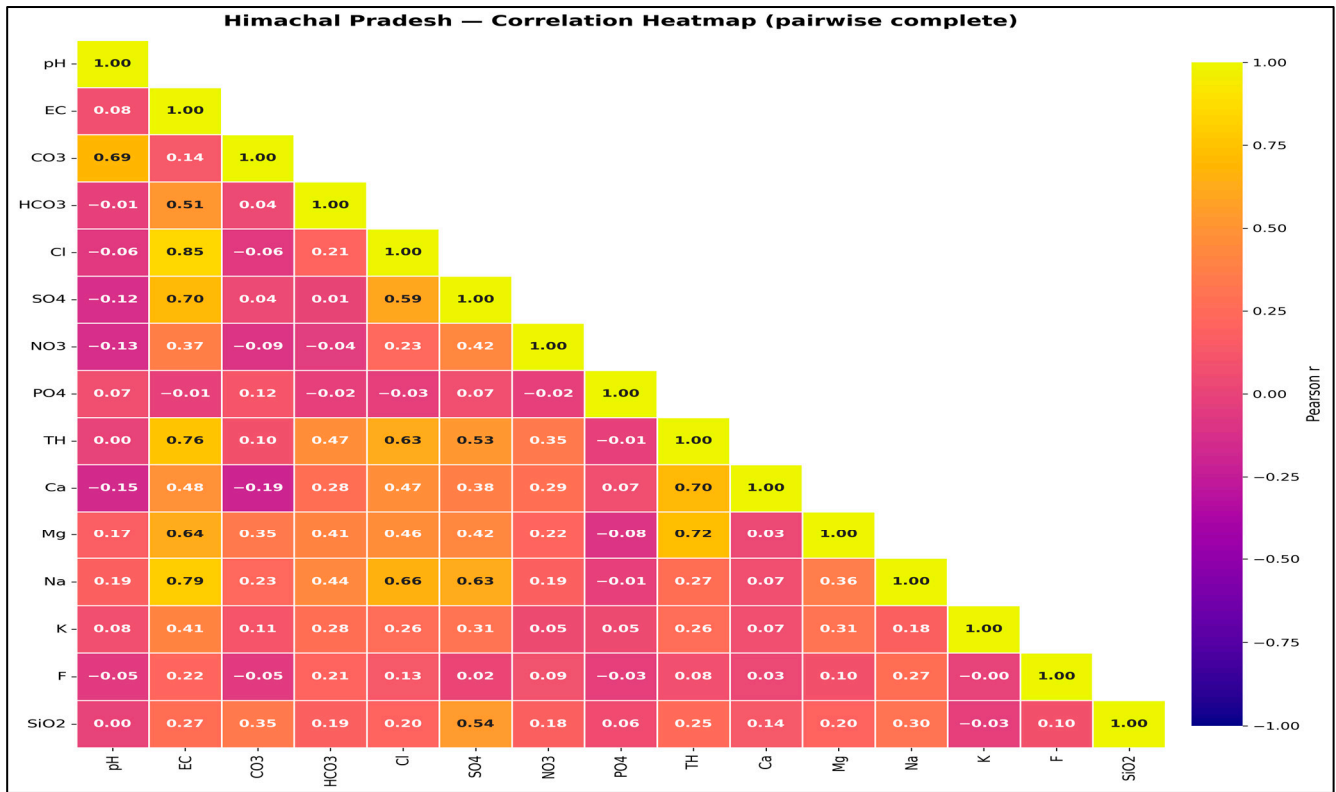
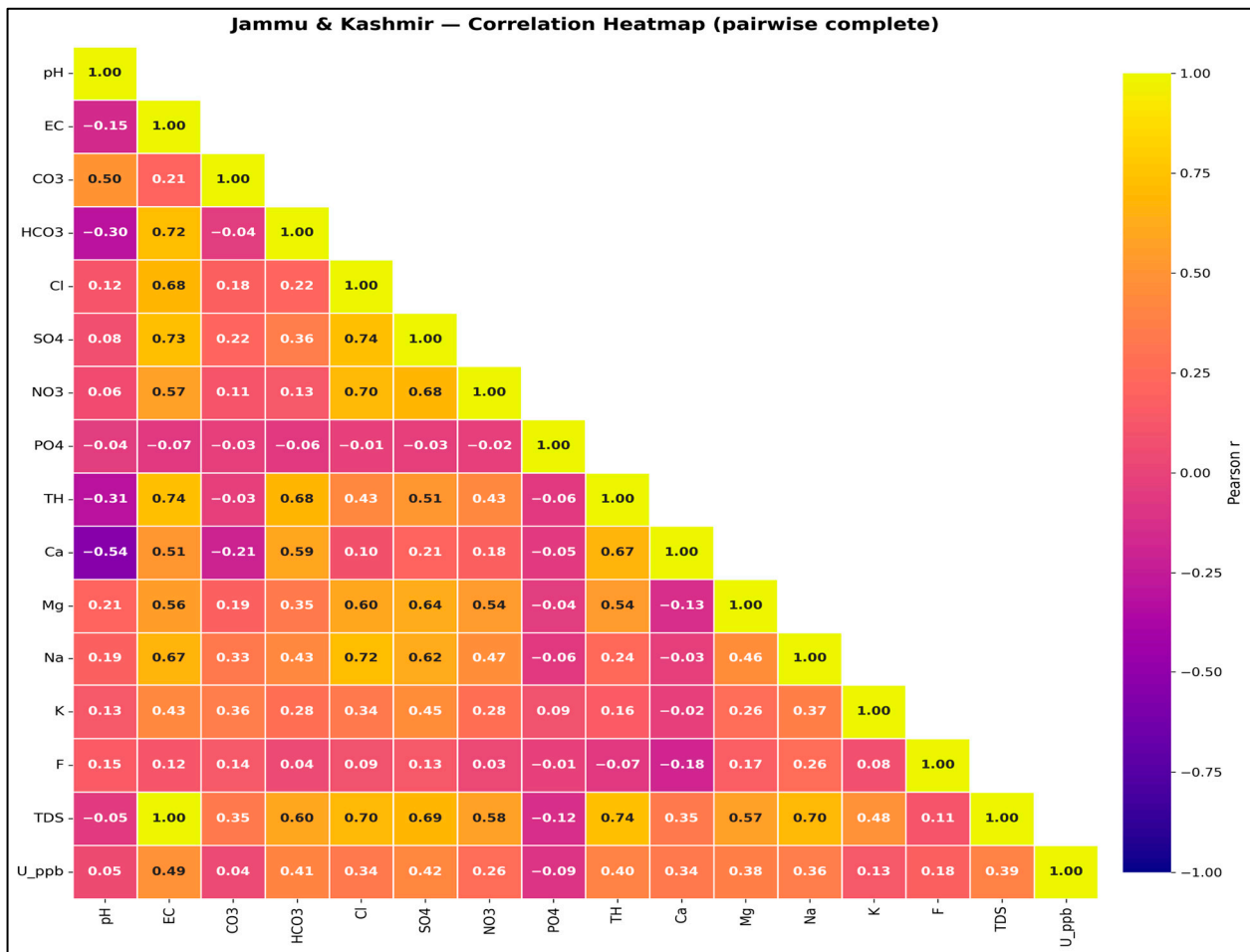


Figure 8. Pearson correlation matrix of physicochemical groundwater parameters in Himachal Pradesh.

For Jammu and Kashmir, the Pearson correlation heatmap (Figure 9) reveals a dense cluster of positive associations centered on EC and TDS and extending to  $\text{HCO}_3^-$ ,  $\text{Cl}^-$ ,  $\text{SO}_4^{2-}$ , hardness,  $\text{Ca}^{2+}$ ,  $\text{Mg}^{2+}$ , and  $\text{Na}^+$ . These relationships indicate that groundwater deterioration in Jammu and Kashmir is primarily linked to cumulative ionic enrichment, with urbanized valley settings and hydrogeochemically complex basins likely intensifying this pattern.

Overall, the results indicate that groundwater quality across the Western Himalayan region remains generally suitable for drinking purposes, although important inter-state variations are evident. Jammu and Kashmir exhibit comparatively greater groundwater stress than Uttarakhand and Himachal Pradesh, as reflected by the higher proportion of poor and very poor WQI classes and the occurrence of extreme WQI observations. In contrast, Himachal Pradesh displays the most stable groundwater-quality conditions, while Uttarakhand shows moderate spatial heterogeneity with localized zones of deterioration. These findings highlight the importance of continued groundwater monitoring and targeted management interventions in districts exhibiting elevated WQI values and stronger hydrochemical enrichment patterns.



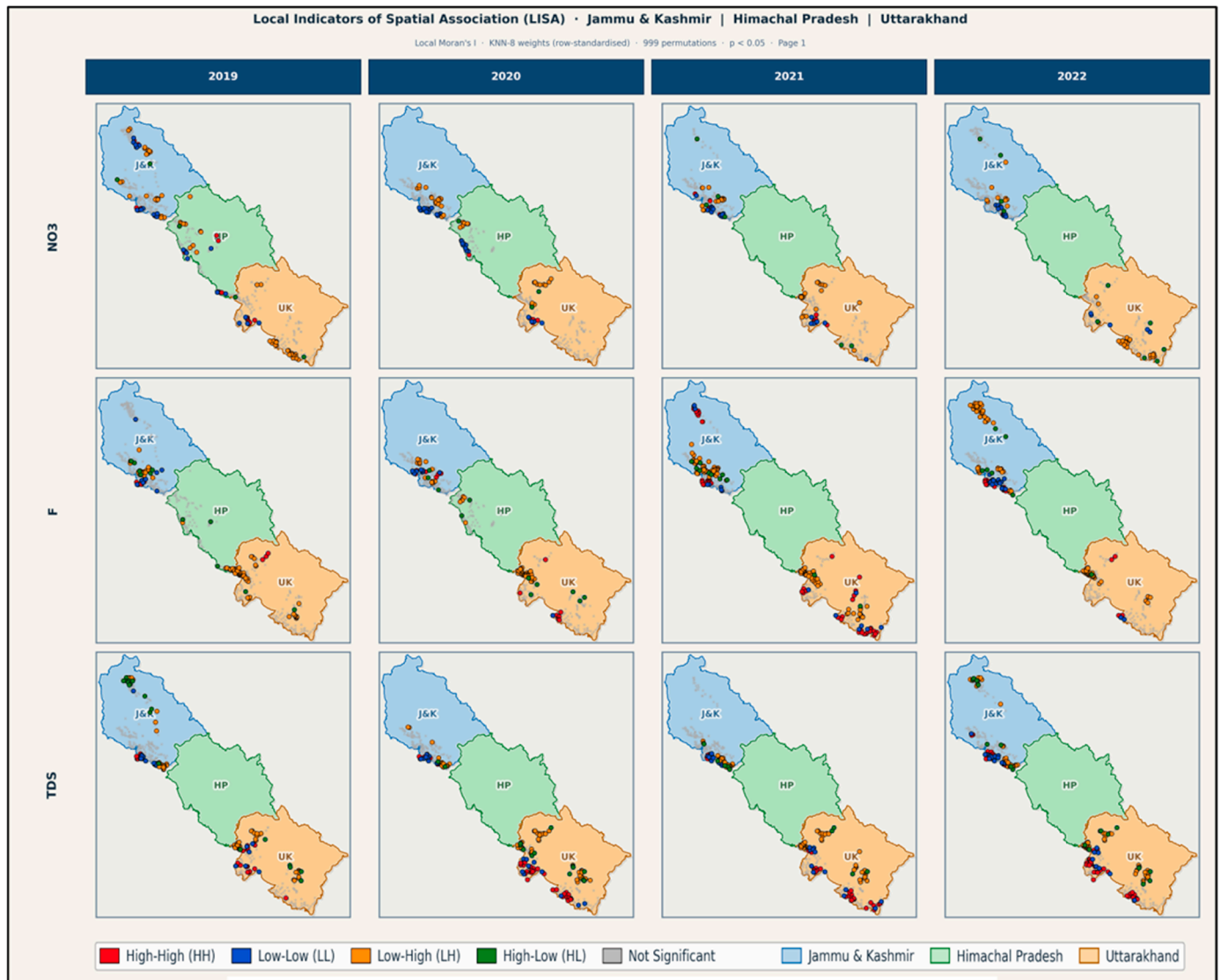
**Figure 9.** Pearson correlation matrix of physicochemical groundwater parameters in Jammu and Kashmir.

### 3.6. Spatial Clustering Patterns of Groundwater-Quality Parameters

The Local Moran’s I (LISA) analysis revealed significant local clusters and spatial outliers for numerous groundwater-quality parameters across the three study regions from 2019 to 2022. In Uttarakhand, the LISA analysis revealed extensive local clustering for several groundwater-quality parameters (Figures 10 and S4–S8). Parameters directly related to geology, such as  $\text{HCO}_3^-$ ,  $\text{Ca}^{2+}$ , and  $\text{Mg}^{2+}$ , consistently formed a large number of High–High (HH) clusters, which were primarily concentrated in the western and southern parts of the state. For example,  $\text{HCO}_3^-$  exhibited 63 HH clusters in 2020 (Figure S6). Alongside these, a significant number of Low–High (LH) clusters were also identified for analytes such as  $\text{Ca}^{2+}$  and TDS, indicating considerable local heterogeneity. The spatial patterns also exhibited notable temporal variation; the number of significant clusters for  $\text{CO}_3^{2-}$ , for instance, fluctuated from 21 in 2019 to a peak of 108 in 2021 before declining sharply to just 10 in 2022 (Figure S7).

In contrast, Himachal Pradesh exhibited fewer and less pronounced significant local clusters than Uttarakhand. A distinctive feature of the spatial pattern in this region was the predominance of Low–High (LH) spatial outliers for many parameters (Figures 10 and S4–S8). In 2019, chloride ( $\text{Cl}^-$ ) had 29 LH clusters, which accounted for the majority of its 47 significant locations (Figure S5). High–High clusters were far less common, although analytes such as EC and  $\text{Na}^+$  each exhibited 10 HH clusters in 2019 (Figures S4 and S6). The temporal coverage of the analysis for Himachal Pradesh was

comparatively limited, as many analytes had an insufficient number of observations ( $n < 8$ ) to be evaluated in 2021 and 2022.



**Figure 10.** LISA-based spatial clustering patterns of nitrate ( $\text{NO}_3^-$ ), fluoride ( $\text{F}^-$ ), and total dissolved solids (TDS) across the Western Himalayas during 2019–2022.

In Jammu and Kashmir, the LISA analysis identified a moderate-to-high number of significant local clusters, indicating distinct spatial structuring for several groundwater-quality parameters (Figures 10 and S5–S9). The region displayed a diverse mix of cluster types. In 2021,  $\text{Ca}^{2+}$  presented a complex pattern with 40 HH and 44 LH clusters (Figure S5), while TDS exhibited 19 HH and 23 LH clusters in the same year (Figure 10). Parameters such as  $\text{HCO}_3^-$ ,  $\text{Ca}^{2+}$ , and total hardness (TH) demonstrated a large number of significant clusters throughout the study period, with  $\text{HCO}_3^-$  showing 100 significant locations in 2019 (Figure S6). Spatially, these clusters were primarily concentrated in the southern and central parts of Jammu and Kashmir.

Taken together, the LISA analysis demonstrates that groundwater quality across the Western Himalayan region exhibits pronounced spatial heterogeneity, with localized clustering patterns varying substantially between states and over time. The parameters presented in Figure 10 ( $\text{NO}_3^-$ ,  $\text{F}^-$ , and TDS) illustrate representative examples of these spatial clustering dynamics, while results for the remaining parameters are provided in Figures S4–S8.

The predominance of High–High clusters for parameters such as  $\text{HCO}_3^-$ ,  $\text{Ca}^{2+}$ ,  $\text{Mg}^{2+}$ , and TDS suggests strong hydrogeological and lithological controls on groundwater chemistry, particularly in mineralized zones. In contrast, the occurrence of Low–High and High–Low outliers reflect localized variability associated with anthropogenic activities, differential recharge conditions, or isolated hydrochemical environments. Temporal fluctuations in cluster intensity further indicate that groundwater-quality dynamics are not spatially static and may respond to changing land-use practices, hydrological conditions, and localized environmental pressures.

#### 4. Discussion

The present study assessed groundwater suitability for drinking purposes across Uttarakhand, Himachal Pradesh, and Jammu and Kashmir, and identified significant spatial and temporal variability in groundwater-quality conditions across the Western Himalayas. The findings indicate that groundwater quality across much of the Western Himalayas remains within excellent-to-good categories, although substantial district-level variability, localized hydrochemical deterioration, and temporal fluctuations were observed across foothill and valley-transition regions. The combined interpretation of WQI patterns, hydrochemical relationships, temporal variation, and LISA-based spatial clustering demonstrates that groundwater-quality variability across the Western Himalayan region is governed by both natural hydrogeological controls and localized anthropogenic pressures.

The predominance of excellent-to-good WQI classes across much of the study region suggests the strong influence of mountain recharge systems, fractured lithology, and relatively limited industrial pressure in upland Himalayan environments. At the same time, the observed spatial heterogeneity demonstrates that groundwater quality is increasingly modified by anthropogenic pressures, land-use transitions, urban expansion, and intensified agricultural activity in foothill and valley settings. The concentration of agricultural and urban land uses within foothill districts and valley environments likely contributes to this pattern by increasing groundwater exposure to fertilizer inputs, wastewater discharge, and other anthropogenic influences. Consequently, variations in land-use intensity may partially explain the observed spatial heterogeneity in groundwater quality across the Western Himalayas [30,37,38]. These findings support the growing body of Himalayan groundwater research emphasizing the coexistence of hydrogeological resilience and localized vulnerability within mountain aquifer systems [29,30,37].

The comparatively stable and low WQI distribution observed in Himachal Pradesh suggests that groundwater chemistry remains primarily controlled by natural hydrogeological processes, including fractured crystalline aquifers, strong precipitation-driven recharge, and relatively low industrial activity in interior mountainous districts. More recently, hydrochemical investigations around Jawalamukhi in Himachal Pradesh reaffirmed that groundwater quality remains predominantly within safe limits, governed mainly by lithological factors [30]. Similar hydrochemical stability has been documented in the Soan Basin of outer Himachal Himalaya, where most groundwater samples were found suitable for drinking, with quality largely controlled by rock–water interaction processes rather than anthropogenic contamination [37]. Comparable results were observed in Kullu Valley, where groundwater quality was largely acceptable, though localized stress was noted near settlements [38]. However, the elevated WQI values observed in Solan and Una indicate that this hydrogeological resilience is spatially uneven. Similar deterioration patterns have been documented in the Baddi–Barotiwalā–Nalagarh industrial belt, where groundwater contamination and associated health risks were linked to industrial effluents and intensified anthropogenic activity [39]. These findings reinforce the emerging understanding that Himalayan foothill transition zones represent hydrochemical stress interfaces where

rapid industrialization, urbanization, and agricultural intensification increasingly modify naturally buffered mountain groundwater systems [30,40,41].

Compared with Uttarakhand and Himachal Pradesh, Jammu and Kashmir exhibit substantially greater hydrochemical heterogeneity and groundwater-quality variability, indicating a more complex interaction between geogenic controls and anthropogenic disturbance. Studies of spring and groundwater systems in Baramulla District revealed a wide spectrum of WQI values, from excellent to moderately degraded, influenced by land-use intensity and settlement density [42]. Broader regional assessments have similarly reported variable groundwater quality conditions across Kashmir, linking elevated nutrient and metal concentrations to urban effluents and agricultural runoff [43]. Hydrochemical evaluation in the Kathua region further confirmed mixed geogenic and anthropogenic influences, with certain pockets exhibiting declining water quality [44]. Similar heterogeneity has been documented in trans-Himalayan Ladakh, where groundwater chemistry is strongly controlled by lithology and climatic aridity but shows localized quality concerns [45].

The wider spread of WQI values and higher proportions of poor groundwater classes suggest that valley-floor aquifers and densely inhabited basins are under comparatively greater environmental stress. Strong associations among EC, TDS, bicarbonate, hardness, calcium, and magnesium indicate that groundwater chemistry across the study region is dominated by coherent hydrochemical evolution associated with mineral dissolution, water–rock interaction, and cumulative mineralization processes, while localized anthropogenic enrichment becomes increasingly pronounced within foothill and valley-transition environments. The pronounced district-level disparities observed in the present study are therefore consistent with the broader Himalayan understanding that intermontane valleys and urbanized basin environments are more susceptible to groundwater-quality degradation than sparsely inhabited upland recharge zones. The LISA-based clustering patterns further reinforce the WQI results by demonstrating that groundwater deterioration is spatially concentrated within foothill and valley-transition districts rather than uniformly distributed across the Himalayan region.

The observed temporal variability in groundwater quality further indicates that Himalayan aquifer systems remain dynamically responsive to changing environmental and anthropogenic conditions. GIS-based WQI assessments in the Basantar watershed demonstrated that spring-water quality remained responsive to catchment conditions [29]. The temporal fluctuations observed between 2019 and 2022 suggest that groundwater-quality conditions across the Western Himalayas respond to changing recharge dynamics, seasonal hydrological variability, and localized anthropogenic pressures. The comparatively greater temporal variability observed in Jammu and Kashmir suggests that valley-dominated aquifer systems may be more sensitive to short-term environmental and land-use changes than relatively stable mountainous recharge environments in Himachal Pradesh and Uttarakhand.

Uttarakhand similarly exhibits predominantly favorable groundwater-quality conditions, particularly within upper and middle Himalayan districts characterized by lower population density and relatively intact recharge environments. Studies in the Kumaun foothills confirm that most groundwater samples fall within acceptable drinking standards, though localized mineral enrichment occurs in transitional zones [36]. Hydrochemical assessments in Dehradun Valley similarly reported largely potable groundwater, while identifying localized anthropogenic signatures in urbanized sectors [31]. The comparatively elevated WQI values observed in Haridwar and Udham Singh Nagar indicate increasing hydrochemical vulnerability within the Tarai–Bhabar and plains-interface regions of Uttarakhand. These districts are also characterized by relatively intensive agricultural activity and higher settlement density than most upland Himalayan districts. Such land-use con-

ditions may enhance groundwater vulnerability through fertilizer application, irrigation return flows, domestic wastewater inputs, and other anthropogenic pressures, thereby contributing to localized hydrochemical deterioration [30,31,36]. Similar hydrochemical deterioration linked to agricultural intensification and expanding urbanization has been documented in foothill environments of the Northwestern Himalayas [30]. Comparable WQI-based investigations in high-altitude lakes such as Dodi Tal and Hemkund have shown that remote recharge environments maintain excellent water quality, emphasizing the protective role of elevation and limited anthropogenic disturbance [21,46].

The broader regional consistency of these findings is further supported by comparable WQI-based groundwater investigations across other Himalayan environments. Studies from Nepal's Himalayan foothills and Arunachal Himalaya similarly reported that groundwater quality generally remains suitable for drinking purposes but becomes increasingly vulnerable within peri-urban and intensively cultivated zones [47,48]. Comparable hydrochemical and multivariate investigations conducted across Himalayan and mountain aquifer systems have also emphasized the growing importance of anthropogenic pressures in modifying naturally mineralized groundwater regimes [6,20]. Collectively, these regional parallels suggest that many Himalayan aquifers exhibit substantial hydrogeological resilience due to strong recharge, fractured lithology, and mountain hydrological dynamics, while remaining increasingly sensitive to localized anthropogenic disturbances and rapidly changing land-use systems.

The findings indicate that groundwater systems across the Western Himalayas remain fundamentally governed by lithological control, recharge intensity, and mountain hydrogeological structure, but are increasingly modified by localized anthropogenic pressures [30,32,36]. The coexistence of generally favorable regional groundwater quality with sharply localized zones of deterioration highlights the fragmented and spatially uneven nature of hydrochemical stress within Himalayan aquifers [30,40,41]. The relative stability observed in Himachal Pradesh and Uttarakhand, contrasted with the comparatively greater variability in Jammu and Kashmir, mirrors conclusions reported across multiple Himalayan hydrochemical investigations [32,36,42–45].

Before considering the broader management implications of these findings, several limitations of the present study should be acknowledged. Although this study integrates multi-year groundwater observations across three Himalayan states, the spatial density and distribution of monitoring wells varied between districts and years, particularly in Himachal Pradesh, where several analytes had insufficient observations during specific monitoring periods. Consequently, localized groundwater conditions in sparsely sampled areas may remain underrepresented. The analysis also relied on secondary groundwater-monitoring data obtained from the Central Ground Water Board (CGWB), which constrained the range of available hydrochemical parameters and precluded assessment of trace metals, microbial contaminants, isotopic indicators, and emerging pollutants. Furthermore, the dataset was based on annual monitoring observations and therefore does not explicitly capture seasonal fluctuations or short-term hydrochemical responses to recharge events and land-use changes. Methodologically, the WQI provides an effective summary measure of groundwater suitability but may simplify complex hydrochemical interactions by integrating multiple parameters into a single index. Similarly, although district-level evaluation and LISA-based spatial analyses provide valuable regional insights, finer-scale hydrochemical heterogeneity within individual watersheds, aquifer systems, and spring catchments may not be fully resolved. These limitations should be considered when interpreting the results and highlight opportunities for future investigations using higher-resolution spatial datasets, seasonal monitoring programs, and expanded hydrochemical characterization.

From a sustainability perspective, these findings demonstrate that groundwater management strategies in mountain environments cannot rely solely on broad regional assessments but instead require district-level monitoring frameworks integrating WQI assessment, multivariate hydrochemical analysis, spatial clustering approaches, and land-use evaluation. Particular attention should be directed towards agricultural and urbanizing foothill districts, where increasing land-use intensity may accelerate groundwater-quality deterioration despite the overall resilience of mountain aquifer systems. Integrating groundwater-quality assessments with land-use information can further assist in identifying emerging contamination hotspots and vulnerable recharge environments. Recent Himalayan groundwater research increasingly emphasizes that proactive protection of recharge zones, strengthened wastewater regulation, and systematic groundwater-quality surveillance in urbanized valleys and foothill transition zones will be essential for sustaining potable groundwater resources under ongoing climatic variability and socio-economic transformation in the Western Himalayan region [9–11].

The present study contributes to the comparatively limited regional groundwater-quality literature available for the Western Himalayas by integrating WQI assessment, hydrochemical relationships, temporal variability, and LISA-based spatial clustering within a unified comparative framework across multiple Himalayan states. Nevertheless, the integration of WQI assessment, hydrochemical relationships, temporal evaluation, and spatial analysis provides a robust regional-scale understanding of groundwater-quality variability across the Western Himalayas and provides an important foundation for future groundwater monitoring and management in mountain environments.

## 5. Conclusions

This study demonstrates substantial regional and district-level variability in groundwater quality across the Western Himalayas based on integrated Water Quality Index (WQI), hydrochemical, temporal, and spatial analyses. Groundwater quality in Himachal Pradesh and Uttarakhand remains predominantly within excellent-to-good categories, whereas that of Jammu and Kashmir exhibits comparatively greater hydrochemical heterogeneity and localized groundwater deterioration. The results indicate that groundwater-quality variability across the region is controlled by the combined influence of hydrogeological conditions and localized anthropogenic pressures, with foothill and valley-transition environments exhibiting comparatively greater vulnerability to groundwater-quality degradation.

The findings further demonstrate that groundwater deterioration is spatially uneven and concentrated within specific hydrogeological and land-use settings rather than being uniformly distributed across the Western Himalayan region. Spatial clustering patterns, hydrochemical relationships, and temporal variability collectively highlight the importance of considering both natural controls and human-induced pressures when evaluating groundwater resources in mountain environments.

From a policy and groundwater-management perspective, the results underscore the importance of establishing district-level monitoring systems that integrate hydrochemical assessment, spatial analysis, and land-use evaluation to identify emerging contamination hotspots and vulnerable recharge environments. Strengthening wastewater regulation, protecting mountain recharge zones, and improving land-use planning in foothill and peri-urban districts will be essential for sustaining groundwater security under ongoing climatic variability and socio-economic transformation in the Western Himalayas.

**Supplementary Materials:** The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/w18131602/s1>, Figure S1: Land-use and land-cover (LULC) map of the Western Himalayan study region; Figure S2: Percentage of missing groundwater-quality observations across physicochemical parameters in Uttarakhand prior to imputation; Figure S3:

Percentage of missing groundwater-quality observations across physicochemical parameters in Himachal Pradesh prior to imputation; Figure S4: Percentage of missing groundwater-quality observations across physicochemical parameters in Jammu and Kashmir prior to imputation; Figure S5: LISA-based spatial clustering patterns of electrical conductivity (EC), pH, and total hardness (TH) across the Western Himalayas during 2019–2022; Figure S6: LISA-based spatial clustering patterns of calcium ( $\text{Ca}^{2+}$ ), magnesium ( $\text{Mg}^{2+}$ ), and chloride ( $\text{Cl}^-$ ) across the Western Himalayas during 2019–2022; Figure S7: LISA-based spatial clustering patterns of sulfate ( $\text{SO}_4^{2-}$ ), bicarbonate ( $\text{HCO}_3^-$ ), and sodium ( $\text{Na}^+$ ) across the Western Himalayas during 2019–2022; Figure S8: LISA-based spatial clustering patterns of potassium ( $\text{K}^+$ ), uranium (U), and carbonate ( $\text{CO}_3^{2-}$ ) across the Western Himalayas during 2019–2022; Figure S9: LISA-based spatial clustering patterns of phosphate ( $\text{PO}_4^{3-}$ ) and silica ( $\text{SiO}_2$ ) across the Western Himalayas during 2019–2022.

**Author Contributions:** Conceptualization, K.P. and S.K.; methodology, F.G. and V.A.; formal analysis, F.G.; investigation, K.P. and S.K.; data curation, F.G. and S.K.; visualization, F.G.; writing—original draft preparation, K.P. and S.K.; writing—review and editing, C.R., N.M., M.P., D.D. and S.K.; interpretation of results, K.P., F.G. and S.K.; supervision, K.P. and S.K. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** The datasets analyzed during the current study are publicly available from the Central Ground Water Board (CGWB), Government of India. Processed datasets generated during this study are available from the corresponding author upon reasonable request.

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