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Identifying lithogenic and anthropogenic factors responsible for spatio-seasonal patterns and quality evaluation of snow melt waters of the River Jhelum Basin in Kashmir Himalaya

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ABSTRACT

The characterization and evaluation of water quality in the Jhelum River Basin is indispensable due to its immense significance in supporting the livelihoods of people and various ecosystem services. Anthropogenic pressures, however, in the form of forest degradation, reckless use of fertilizers and pesticides, land system changes and unplanned settlements are diminishing pristine basin water quality, which necessitates better understanding of pollution variability and its sources. Extensive field sampling across major tributaries and along main river course was carried out during the year 2017–18. Pattern recognition techniques like Hierarchical Cluster Analysis (HCA), Wilk's λ quotient, Principal Component Analysis (PCA) and Analysis of Variance (ANOVA) were applied to a huge dataset comprising of 5192 observations. Spatially, three clusters correspond to low pollution headwater streams (cluster 1), moderately polluted middle and downstream sites (cluster 2) and high polluted main river course sites (cluster 3). This is also supported by ANOVA results, manifesting significantly higher concentrations of total hardness (TH), calcium (Ca), magnesium (Mg), chloride (Cl), total alkalinity (TA), nitrate-nitrogen (NO_3-N), total phosphorus (TP), iron (Fe) and total coliform (TC) in high pollution associated cluster (cluster 3) followed by cluster 2 and minimum quantities were observed in cluster 1. Observations on seasonal water quality either did not fluctuate considerably or differs significantly during summers only, except water temperature (WT), which exhibits significant difference in all seasonal clusters. Wilk's λ quotient distribution revealed that only WT was main contributor in the formation of seasonal clusters. PCA recognized five underlying factors in the data structure and explained about 72% of total variance. Maximum variance (22.66%) is explained by combination of ionic salt group (natural source) and TC (anthropogenic source) followed by dissolved ions (19.20%) causing hardness and buffering of waters, nutrient sources (15.08%) from human and agriculture wastes, gradient factor (7.87%) allied with small fall in dissolved oxygen (DO) downwards and pH (7.11%) linked with hydrolysis of acidic material accrued from organic matter. The water quality index (WQI) was mostly influenced by coliform bacterial count and pH with highest mean effective weights of 39.15% and 26.65% respectively. Evaluation of the water suitability for drinking purpose reveals that the Jhelum River Basin has mostly retained excellent water quality (66% of data points) but poses safety concerns in downstream segments due to anthropogenic signatures.

1. Introduction

Globally the Himalayan water quantity and quality are viewed as the most significant as well as sensitive issues vis-à-vis human well-being and ecological integrity (Barnett et al., 2005; Vörösmarty et al., 2010). Even though the Himalayas contribute only 4% to the global land surface, but they generate about 25% of total dissolved loads emptying into oceans (Raymo and Ruddiman, 1992). During past decades, investigations related to hydro-chemical characteristics in the Himalayan regions have attributed to the deterioration of surface water quality resulting in increase in temperature, variability in precipitation, intense urbanization and deforestation, poor land system changes and exploitation of mineral resources (Sun et al., 2012; Wu et al., 2012). Particularly, the rivers and their tributaries that flow across the cities of South Asian developing countries like India, Nepal, Bangladesh and Pakistan (Karn and Harada, 2001; Kambole, 2003; Pekey et al., 2004; Richardson et al., 2015; Mir et al., 2016).

River basin research studies furnish unique insights into individual

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catchment hydrological functions, because hydro-chemical characteristics of rivers are regulated through intricate relationship among different chemical, physical and biological environments (Brezonik and Arnold, 2011; Shi et al., 2017). Viewing the importance of river water quality for domestic, ecological and economic stability, hydrochemistry and underlying processes controlling it in the world's major rivers have been elucidated well in the past, notably the River Amazon (Stallard and Edmond, 1987), Nile River (Dekov et al., 1997), Mississippi River (Sharif et al., 2008), Tigris River (Varol et al., 2012), Indus River (Ahmad et al., 1998), Yellow River (Zhang et al., 1995), Mekong River (Huang et al., 2009; Whitehead et al., 2019), Yangtze River (Huang et al., 2009; Jiang et al., 2015), the Ganges, Brahmaputra and Yamuna Rivers (Sarin et al., 1989; Dalai et al., 2002). The above investigations not only have documented different sources and factor guiding mechanisms of hydro-geochemistry in these river basins but have also provided a vast and significant evidence about patterns and rates of dissolved chemicals in continent-river-ocean system (Pant et al., 2018).

The River Jhelum in the north western Kashmir Himalaya forms a major tributary of the Upper Indus Basin, and offers an important link for various geochemical processes while delivering substantial quantities of geogenic and anthropogenic material to the ocean (Mir et al., 2016). The dissolved solid loads of Jhelum River and its tributaries have been reported to be inversely proportional to altitudinal gradient of streams (Jeelani et al., 2011). The study also described calcite dissolution as dominant process in controlling surface water chemistry. The alkaline nature of Jhelum basin water quality (WQ) with Ca^{+2} and HCO_3^- dominating cationic and anionic budgets respectively, correlates with the diverse lithology of the basin (Mir and Jeelani, 2015b). Pertinently, just like other Himalayan Rivers, snow and glaciers remain extensive sources of runoff to Jhelum River Basin (JRB) streams. The major western Himalayan Rivers, of which the JRB is a part, are recipients of significant amount of melt waters from snow and ice reserves (Immerzeel et al., 2010). Nevertheless, snow and glaciers of Himalayan region in response to present warming climate are experiencing significant shrinkages (Singh et al., 2016; Rashid et al., 2017a,b; Farooq et al., 2018). This warming pattern of climate can elevate the ion and nutrient pollution loads in rivers through variation in precipitation and resulting discharge patterns. For instance, the lower discharge of rivers in summers would provide lesser amount of dilution effect to ions and nutrients and thereby enhances their concentrations (Whitehead et al., 2006). Similarly, the more frequent downpour events and floods become, the more it will increase the erosion and runoffs, which subsequently augment nutrient pollution in the river waters (Jeppesen et al., 2009). Besides, accelerated dynamics of hydro-chemistry by varying climatic conditions and geology of region, the Jhelum River Basin (JRB) is also influenced with anthropogenic activities, especially towards middle and downstream segments. The waters of Vishav stream, a tributary of Jhelum, progressively reflected anthropogenic pressures from higher to lower gradients with inputs from agricultural lands, urban surfaces and domestic sewage discharge (Hamid et al., 2016). Deterioration of water quality in Lidder stream of Kashmir Himalaya is attributed to tourism influx in summers besides widespread usage of fertilizers and pesticides in horticulture and agriculture lands during this time (Rashid and Romshoo, 2013). Further, the study also mentioned an increasing nutrient concentrations in the form of phosphorous and nitrogen as agents of water quality impairment. Likewise, hydro-physicochemical characterization of Dagwan stream- tributary of Jhelum, revealed higher levels of organic and inorganic parameters during peak flow times due to more intensive runoffs. However, the WQ were within permissible limits for desired uses like drinking, irrigation, washing, agriculture, and fisheries (Sabha et al., 2019). A three decadal comparison of WQ parameter results of the Jhelum River revealed a very high (260%) increase in nitrogen nutrient forms but a moderate rise in dissolved solids (33%) and conductivity of water (22%) (Rather et al., 2016). Such elevated levels of WQ parameters are attributed to population growth expansion in the basin (estimated to be 6.9 million), forest degradation and deforestation (J&K Census, 2011, Romshoo and Muslim, 2011; Romshoo and Rashid, 2014). Apart from above studies, mixing processes cause a significant spatial and temporal variability of hydrochemistry in Jhelum basin waters (Mir et al., 2016).

In light of remarkable economic significance ranging from domestic, industrial, irrigation to hydro power generation in the region and the fact that JRB waters are under continuous threat from various developmental activities, the hydro-geochemical evaluation with space and time could infer about present operating processes in the basin and therefore would help in establishing sustainable measures to undo the causes of WQ deterioration. Additionally, mountain river ecosystems of the Kashmir Himalaya hosts a significant biological diversity and is directly linked with the WQ of these environs. To recognize major contributors in spatiotemporal variability of waters, assessment of WQ is critical as it benefits water resource management. Also, based on information from assessments, the public gets sufficiently aware to carry out protective measures in order to improve the condition of river systems. Therefore, research studies on hydro-chemical characterization and repercussions of natural and anthropogenic origin contaminants are imperative to elucidate and safeguard the JRB water quality. However, only a limited research dataset is available that is either related to Jhelum River stretch only or of few tributaries or distributaries, thus representing a significant knowledge gap in comprehending hydro-chemical characterization of the basin and its tributaries as a single unit for study. In this context, the present research is aimed to study the spatial and seasonal patterns of hydro-chemical parameters and the underlying factors accountable for such variability in these patterns. Since the JRB is the lifeline of Kashmir Valley and fundamentally accomplishes drinking water necessities, the river water suitability for human consumption was also assessed by a comprehensive water quality index (WQI). We have focused here on an efficient approach for the determination of WQI based on key selected WQ parameters using PCA and correlation techniques. Such an index could diminish redundant information and also analytical measurement costs, particularly in developing nations. Moreover, this index can be a beneficial tool in facilitating the work of decision makers in Himalayan regions.

Specifically, the objectives of the present study were: (1) to determine how hydrochemistry varied spatio-seasonally among different streams/rivers of the JRB; (2) to identify the underlying factors responsible for causing such a characterization and (3) to evaluate a comprehensive water quality index (WQI) for drinking water purpose.

2. Study area

The Jhelum River Basin is located in the Union territory of Jammu and Kashmir towards northern India with dimensions of 130 km length and 40 km width and consists of about 15,000 km^2 drainage area. The basin possesses a main drainage channel in the form of Jhelum River, besides having a fairly well-established drainage system. It is encompassed by Pir Panjal mountains in the southwest and Greater Himalaya mountain range in the northeast (Fig. 1). Eleven tributaries drains each of the two surrounding mountain ranges and radially confluence the main trunk of River Jhelum (Bhat et al., 2019). Previous studies have regarded a spring at Verinag, Anantnag towards south-eastern part of the Kashmir as the origin of the River. However, the present research affirms Lidder stream to be the origin of the Jhelum River, being the longest drainage channel wherefrom water source-point commences. The River then meanders through central city (Srinagar) of Valley before it enters into Wular lake in the northwestern direction. After exiting from the lake, the river cuts across Pir Panjal through Baramulla-Uri gorge and then flows into Muzaffarabad. The Jhelum waters harbor a rich resource of fisheries besides serving as drinking water and agriculture sustenance in its catchment and, therefore, has tremendous socio-economics linked to it (Rather et al., 2016).

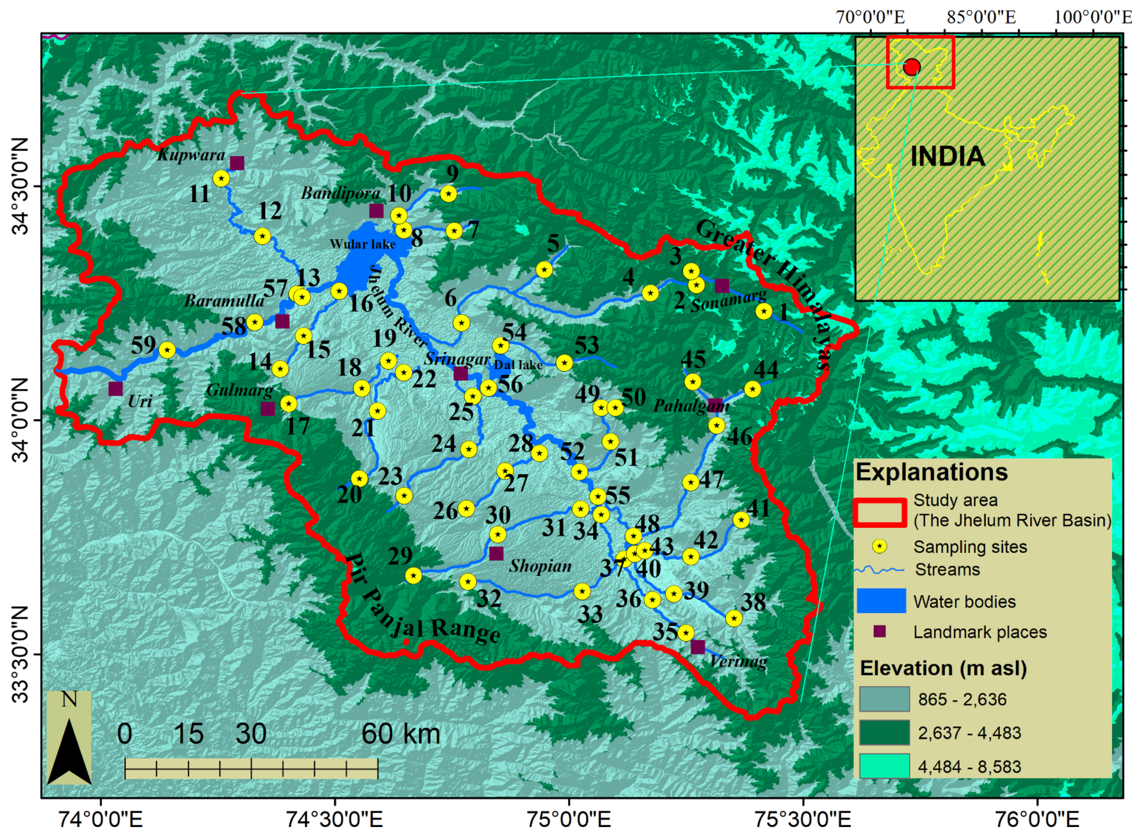

Fig. 1. Location map of study area – the Jhelum River Basin, its major tributaries and 59 investigated sampling sites.

Geologically, the basin is characterized by heterogeneous rock types including Agglomeratic slate, Panjal traps, Gneissose granite, Shale, Quartzite inclusions, Limestone, Karewa formations and River alluvium (Wadia, 1975; Bhatt, 1989). Land use and land cover of the whole basin consists of agriculture (20.35%), aquatic vegetation (0.89%), barren land (12.8%), built-up (1.70%), forests (29.59%), scrub land (13.81%), pastures (4.2%), horticulture (5.71%), plantation (6.49%), snow & glacier (3.38%) stream bed (0.57%) and water (0.52%) (Murtaza and Romshoo, 2014). The climate of the region is of sub-humid temperate type with unpredictable weather conditions owing to its rugged topography. Based on the mean temperature and precipitation, climate of the basin has been broadly categorized into four seasons, i.e., summer (June to August), autumn (September to November), winter (December to February) and spring (March to May). Annual temperature in the Kashmir valley varies from about −10 °C (winter) to 35 °C (summer). Linked with western disturbances, precipitation in the region remains maximum during the winter and spring time (Dar et al., 2015). During the current study, maximum precipitation was observed in spring (1552 mm), followed by summer (1152.1 mm), winters (764.6 mm). It was found to be the least in autumn season (202.2 mm) (Digest of Statistics, 2017).

3. Methodology

3.1. Selection of sampling sites

Fifty-nine sampling sites were selected to represent the main course and all the 18 major tributaries across the right and left side of the Jhelum River (Fig. 1). Sampling points were selected taking into consideration the accessible head water stream points (Alt. 2848-1743(m)), midstream locates (Alt. 2014-1676(m)) and downstream sites (Alt. 1604-1581 (m)). Moreover, some assessment sites were also taken along the main path of the Jhelum river (Alt. 1601-1367 (m)). In order to observe clear water quality changes and impact of pollutants, WQ assessment was performed in four seasons from summer 2017 to spring 2018, wherein a total of 236 water samples were obtained and analyzed. A portable GPS was used to measure the geographical position of sampling sites. Sampling, preservation and transportation of samples to the laboratory was performed as per the standard methods (APHA, 2017).

3.2. Analytical procedure

Measurements of water temperature (WT), pH, conductivity (Cond), total dissolved solids (TDS) were carried out with a multi-parameter probe (Eutech PCSTEST35-01x441506/Oakton 35425-10), calibrated with standard solutions. The accuracy details of the multi-probe parameters stands herein as WT (± 0.2 °C), pH (± 0.01), conductivity and TDS (± 1% FS). The other WQ parameters were analysed in the laboratory following the standard protocols (APHA, 2017). Dissolved oxygen (DO) was determined by Winkler's method, total hardness (TH), calcium ion (Ca^{+2}), magnesium ion (Mg^{+2}) by the EDTA titrimetric method, total alkalinity (TA) and free carbon dioxide (FCD) by titration method, chloride ion (Cl) by the argentometric method and total coliform (TC) through multiple tube fermentation method. The parameters that were analysed spectrophotometrically include: nitrate- nitrogen (NO_3-N) (salicylate method), nitrite-nitrogen (NO_2-N) (colorimetric method), ammoniacal-nitrogen (NH_3-N) (phenate method), ortho-phosphate phosphorus (OP) (stannous chloride method), total phosphorus (TP) (sulphuric acid-nitric acid digestion method), sulphate (SO_4^{-2}) (turbidimetric method), dissolved silica (DS) (molybdosilicate method) and total iron (Fe) (phenanthroline method). Furthermore, water samples, collected in the field, were checked for any discrepancy and quality using standard operating procedures, calibrated with standards, controls and analysis of reagent blanks. Precision and bias are two indicators of measurement quality to assess validity of the analytical processes. The relative standard deviation (RS) and relative error (RE) (as precision and bias indicators) of various parameters are as: hardness parameters (RS = 2.9%; RE = 0.8%), Cl (RS = 4.2%; RE = 1.7%); DS (RS = 8.4%; RE = 4.2%); NO_3-N (RS ≤ 1%); NH_3-N (RS = 28.6%; RE = 5%); OP (RS = 25.5%; RE = 28.7%) and TP (RS = 20.8%; RE = 1.2%) (APHA, 2017).

3.3. Statistical methods for data analysis

Analysis of variance (ANOVA) was performed on water quality datasets to determine differences among three spatial clusters (cluster1, cluster 2 and cluster 3) and three seasonal clusters comprising of autumn and winter (together), spring and summer respectively. In case the between-subject effects of the ANOVAs were found to be significant, pairwise comparisons in spatial clusters and seasonal clusters were carried out. These comparisons were achieved with Tukey's HSD (honestly significant difference) multiple comparison procedure.

To examine the suitability of datasets for PCA, Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests (BST) were performed (Shrestha and Kazama, 2007; Varol and Sen, 2009). KMO is a measure of sampling adequacy, illustrating percentage of common variance that might be produced by underlying factors. A high value (close to 1) generally is a sign for suitability of PCA (principal component analysis), as was found in present study, where KMO = 0.826.

$$KMO = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} p_{ij}^2} \quad (1)$$

where r_{ij} is the correlation matrix and p_{ij} is the partial correlation matrix.

BST is used to express if a correlation matrix is an identity matrix, which would specify that the variables are not related (Shrestha and Kazama, 2007). BST can be formulated as:

$$BST = \frac{(N-k)\ln(S_p^2) - \sum_{i=1}^{k}(N_i-1)\ln(S_i^2)}{1 + \frac{1}{3(k-1)}\left(\sum_{i=1}^{k}(1/N_i - 1) - \frac{1}{N-k}\right)} \quad (2)$$

where N is the total sample size, k denotes the number of groups, N_i represents the sample size of the ith group, S_i^2 is the variance of the ith group and S_p^2 is the pooled variance.

Multivariate statistical techniques like Hierarchical Cluster analysis (HCA) and Principal Component Analysis (PCA) (Panda et al., 2006; and Mei et al., 2014) were applied on the water quality data, standardized through z-scale transformation, to evade any misclassification due to large differences in dimensionality of data (Singh et al., 2005; Varol et al., 2012). Moreover, standardization method makes the data dimensionless by eliminating effects of various measurement units and parameter variances (Zhou et al., 2007). Box plots, presenting more than one statistics (Norusis, 1993; Vega et al., 1998), were utilized to distinguish WQ parameters in different spatial clusters and seasons. Further, the spatial cluster and WQI distribution maps were prepared in a GIS environment.

3.3.1. Hierarchical Cluster Analysis (HCA)

HCA, an eminent environmetric pattern recognition method, assembles objects into groups (clusters) according to their independent attributes or characteristics. The categories of objects so produced reveal homogeneity within clusters and heterogeneity between clusters (McKenna, 2003). CA furnishes a dendrogram which delivers a graphic summary of clustering process (Singh et al., 2004). CA was employed to describe spatio-temporal variations in 22 water quality datasets using Ward's method (Ward, 1963) and the squared Euclidean distance algorithm (Shrestha and Kazama, 2007).

3.3.2. Wilk's lambda quotient distribution

After the formation of cluster groups, Wilk's λ distribution (Wilks, 1932) was used to determine the influence of each parameter in the formation of a cluster. Wilk's λ quotient for each water quality parameter from each sampling site is consigned, using below equation:

$$\lambda = \frac{\sum_i \sum_j (x_{ij} - \bar{x}_i)^2}{\sum_i \sum_j (x_{ij} - \bar{x})^2} \quad (4)$$

where x_{ij} is the j^{th} element of the i^{th} cluster, $\bar{x}i$ the ith cluster's mean and $\bar{x}$ the total mean. The value of λ implies the within-cluster sum of squares to the total sum of squares ratio. The value of λ ranges between 0 and 1. Smaller the λ value is, the more it determines the cluster formation (Afifi et al., 2004; Hatvani et al., 2011).

3.3.3. Principal Component Analysis (PCA)

PCA is the most consistent pattern recognition method used to procure information by changing original, interrelated parameters into fewer uncorrelated (orthogonal) variables referred to as principal components (PCs). The input variables of PCA are correlated whereas the hypothetical parameters (PCs) are orthogonal and are acquired as a linear combination of the experimental variables (Hatvani et al., 2014). The correlation coefficients obtained from original variables and principal components furnishes the factor weightings (loadings) which defines the weights of the PCs in the original variables. In the entire dataset, PCA extracts information, through data reduction, on the most significant variables without losing any original information (Helena et al., 2000; Vega et al., 1998). The PC can be computed as:

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + \cdots + a_{im}x_{mj} \quad (5)$$

wherein z symbolizes component score, a indicates component loading, x designates measured value of variable, i is the component number, j infers the sample number and m implies total number of variables (Juahir et al., 2011).

3.4. Calculation of water quality index (WQI)

WQI is a very beneficial and suitable method for assessing the quality of water and is very often utilized by researchers and water quality managers (Sánchez et al., 2007; Rashid et al., 2017a,b; Sener et al., 2017; Khanday et al., 2018). It is a rating that mirrors the combined impact of various WQ parameters (Sánchez et al., 2007) and its appearance beyond a certain threshold value limits the drinking usage of water (Varol and Davraz, 2015). To every WQ parameter, different weights were provided stretching from 1 (least effect on WQ) to 5 (highest effect on WQ) based on their apparent primary health impacts. Computation of WQI is expressed by the following equations:

$$Rw_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (6)$$

where R*wi* designates relative weight, *wi* shows each WQ parameter weight and n denotes the total number of WQ parameters. Thereafter, for every WQ variable, a quality rating is assigned as below:

$$Qr_i = \frac{C_i}{S_i} \times 100 \quad (7)$$

where Qr_i is the quality rating, C_i indicates WQ parameter concentration in each sample and Si represents the drinking water standard for each parameter as per the guidelines of Bureau of Indian Standards (BIS) and Environmental protection agency (EPA) (2012). Then, for WQI calculation, first sub-index (SIi) is estimated as:

$$SI_i = Rw_i \times Qr_i \quad (8)$$

$$WQI = \sum_{i=1}^{n} SI_i \quad (9)$$

wherein, SIi specifies the sub-index of ith parameter, relative weight and quality rating of ith parameter are symbolized by Rwi and Qri respectively. The computed WQI values are categorized into five classes

Table 1
Descriptive statistics of 22 stream water quality (WQ) parameters measured at 59 locations of the Jhelum River Basin.

Parameters	Abbreviations	Units	Minimum	Maximum	Mean	Standard Deviation
Water temperature	WT	°C	2	28	8.82	5.47
Velocity	Vel	m/s	0.1	2.5	0.92	0.46
Discharge	Dis	m^3/s	0.1	218	28.23	45.70
pH	pH	–	6.9	9.1	8.06	0.36
Conductivity	Cond	µS/cm	35	666	212.62	122.54
Dissolved oxygen	DO	mg/L	5	11.9	8.37	3.66
Total dissolved solids	TDS	mg/L	9	472	149.25	86.67
Total hardness	TH	mg/L	42	204	111.19	34.25
Calcium ion	Ca	mg/L	9	50	28.39	8.75
Magnesium ion	Mg	mg/L	3	19	9.94	3.51
Total alkalinity	TA	mg/L	24	168	82.58	28.53
Free carbon dioxide	FCD	mg/L	0.5	8.8	3.17	1.60
Nitrate nitrogen	NO_3-N	µg/L	14	737	160.06	103.46
Nitrite nitrogen	NO_2-N	µg/L	3.28	257.21	42.66	29.01
Ammoniacal nitrogen	NH_3-N	µg/L	15.01	312.3	75.17	47.66
Ortho phosphate	OP	µg/L	10	297	46.52	37.86
Total phosphorus	TP	µg/L	30	554	140.70	106.52
Sulphate ion	SO_4^{-2}	mg/L	1.16	42	15.99	8.98
Dissolved silica	DS	mg/L	1	28	5.92	6.14
Total iron	Fe	µg/L	9	54	23.95	9.73
Chloride ion	Cl	mg/L	5	38	17.70	7.03
Total coliform	TC	MPN/100 ml	0	880	113.46	171.51

as: < 50 denotes excellent water; 50–100 represents good water; 100–200 signifies poor water class; 200–300 expresses very poor water category and > 300 specifies the water class which is unhealthy for drinking (Sánchez et al., 2007, Yidana and Yidana, 2010, Sener et al., 2017).

Further, to investigate influence of any water quality parameter on WQI, the effective weights of every WQ parameter were evaluated by using the equation:

$$Ef_i = \frac{SI_i}{WQI} \times 100 \tag{10}$$

where, Efi indicates the effective weight of ith parameter, SIi represents sub-index of ith parameter and WQI denotes the water quality index calculated by Eq. (9).

4. Results and discussion

4.1. General description of the stream water quality (WQ) parameters

The descriptive statistics of all the investigated WQ parameters from 59 sampling sites is summarized in Table 1. Water temperature in the Jhelum basin river tributaries ranged from 2 °C to 28 °C. Velocity varies from 0.1 to 2.5 m/s while discharge differs greatly from 0.1 to 218 m^3/s with a mean value of 28.23 m^3/s. The values for pH and conductivity of all sampling points fluctuate from 6.9 to 9.1 and 35 to 666 µS/cm, respectively, during the surveillance period. DO showed variations from 5 to 11.9 mg/L with a mean value of 8.37 mg/L. A wide variation of 27–472 mg/L was noticed in TDS. The waters of tributaries were observed to be hard and well buffered having average values of 111.19, 28.39, 9.94 and 82.54 mg/L for TH, Ca, Mg and TA, respectively. FCD of waters was found in the stretch of 0.5 to 8.8 mg/L. Among the nutrient (nitrogen and phosphorus) forms, NO_3-N and TP showed dominance with a mean value of 160.06 and 140.70 µg/L, respectively. SO_4^{-2} and DS exhibited mean values of 15.99 and 5.92 mg/L. Similarly, Fe and Cl revealed average values of 23.95 µg/L and 17.70 mg/L in the waters. The presence of TC in the basin stream waters varied from 0 to 880 MPN/100 ml.

4.2. Spatial pattern analysis and Wilk's lambda

Spatial variations in WQ parameters of sampling sites were detected by using cluster analysis (CA). It rendered a dendrogram (Fig. 2) grouping all 59 sampling points into three distinctive clusters and the sites in each cluster possessing identical characteristic features and natural background processes. Maximum of sites (33) retained in cluster 1 correspond to relatively low pollution headwater streams while as cluster 2 which retains 22 sites is associated with moderately polluted middle and downstream sites. And finally, cluster 3 that contains 6 sites, is allied with high polluted main river course sites (Fig. 3). Apparently, the results of ANOVA (Table 2) manifest significant difference in WQ parameters viz., TH, Ca, Mg, Cl, TA, NO_3-N, TP, Fe and TC among the three clusters. The concentration of these parameters remains highest in cluster 3, followed by cluster 2 and is least in cluster 1. Because of the longitudinal gradient of streams, the sites of cluster 3, located on the main trunk of Jhelum river, remain under direct human impact as most of untreated sewage drains emptying into the river directly and thus augments the magnitude of above WQ parameters (Mir and Jeelani, 2015a; Meraj et al., 2015). Further, the solid waste collection along the river peripheries is poorly serviced which can be understood from the fact that only about 25% of solid waste from all zones of Srinagar city gets collected through door-to-door service (Nengroo et al., 2017) and the remaining is dumped by road-side which subsequently finds way to river waters and thus adds-up nutrient level. Since the sites included in cluster 2 are either related with agricultural/horticultural wastes like fruit and vegetable residues or are under the influence of sparse human settlements and, therefore, showed moderate level of parameter concentration. The sampling sites (headwater points) which encompass cluster 1 are least impacted by any activity except animal wastes and, therefore, have a near natural concentration level of parameters. Compared to clusters 2 and 3, the velocity of water in cluster 1 differs considerably owing to its higher gradient. Water discharge was found significantly higher in cluster 3 due to high depths and contribution from all the tributaries forming the river. pH of water towards main river showed significant decrease because of hydrolysis of acidic material accumulated from raw drainage wastewater (Singh et al., 2005). In comparison to middle and downstream sites (cluster 2 and 3), the concentration of DO was effectively higher in upper reach streams (cluster 1) due to negligible human interference and, thus, little organic matter is to be mineralized which consumes less oxygen. An insignificant difference is depicted by conductivity and TDS between clusters 2 and 3 but differs significantly with cluster 1. It suggests that, in addition to naturally occurring ions from weathered material, middle and downstream sites possess much more ion concentration from other sources like mineralization of bulk organic matter, which headwater

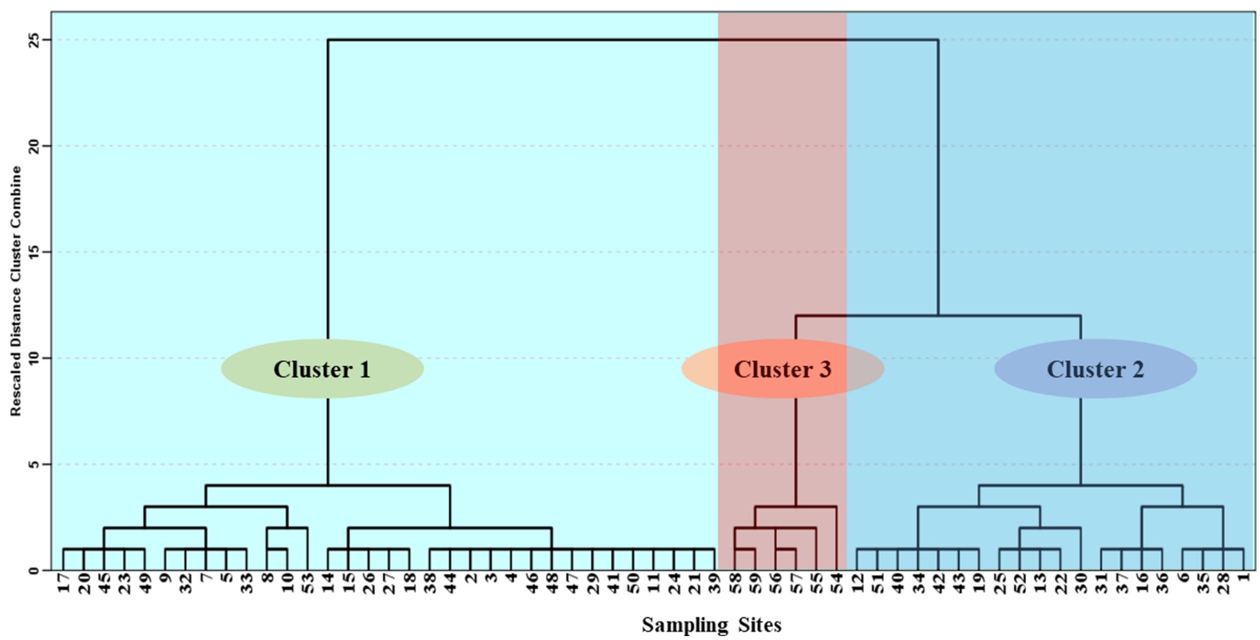

Fig. 2. Dendrogram of spatial (site) cluster analysis revealing three distinctive clusters.

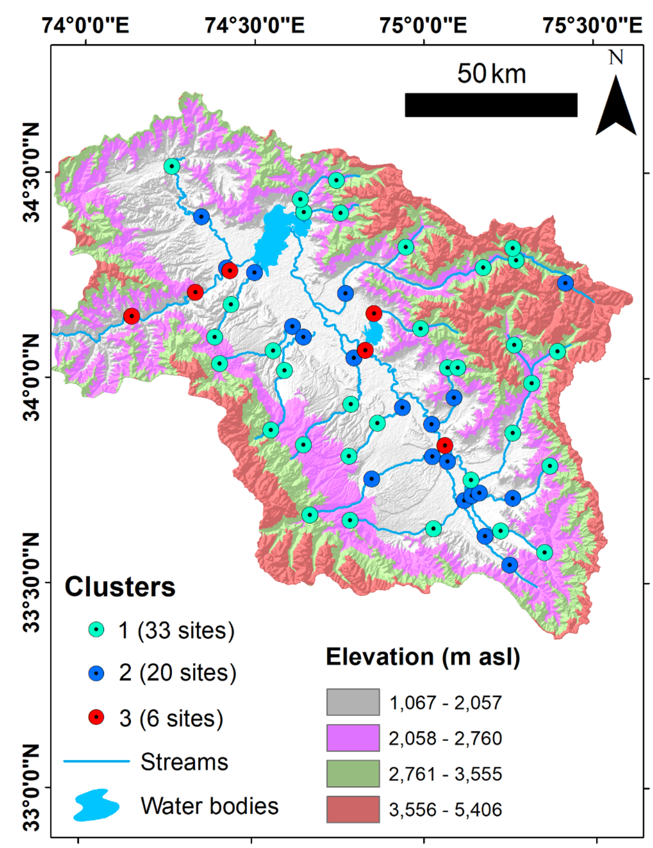

Fig. 3. Spatial display of sites included in the three clusters as assembled by cluster analysis.

streams are deficient of and, consequently, retain less ion quantity.

The Wilk's λ lowest quotient values were held by DS (0.225), Dis (0.321), TC (0.331) and parameters which cause hardness and buffering of waters such as TH (0.404), Ca (0.446), TA (0.503), Mg (0.554) and Cl (0.567). These were followed by another group of parameters retaining even higher values which includes nutrients like - TP (0.604), NO_3-N (0.657) and dissolved solids (0.641), Cond (0.635), FCD (0.705), Fe

Table 2
Clusters of sampling sites showing mean values with standard errors (S.E) and ANOVA for WQ parameters. Different letters (italic) indicate statistical difference at $P < 0.05$ among clusters with Tukey's HSD test.

Parameters	Cluster 1		Cluster 2		Cluster 3	
	Mean	S.E	Mean	S.E	Mean	S.E
WT	8.27 *(a)*	0.47	9.32 *(a)*	0.68	10.17 *(a)*	0.69
Vel	1.05 *(b)*	0.04	0.80 *(a)*	0.05	0.61 *(a)*	0.06
Dis	14.48 *(a)*	1.41	17.45 *(a)*	2.12	139.82 *(b)*	13.11
pH	8.13 *(b)*	0.03	8.00 *(ab)*	0.04	7.89 *(a)*	0.06
Cond	147.31 *(a)*	7.18	300.80 *(b)*	14.16	277.87 *(b)*	12.32
DO	9.56 *(b)*	0.38	6.98 *(a)*	0.16	6.44 *(a)*	0.13
TDS	103.35 *(a)*	5.19	210.70 *(b)*	9.91	196.83 *(b)*	8.91
TH	90.95 *(a)*	1.96	125.90 *(b)*	2.15	173.42 *(c)*	5.39
Ca	23.48 *(a)*	0.53	31.82 *(b)*	0.59	44.00 *(c)*	1.34
Mg	8.11 *(a)*	0.23	11.30 *(b)*	0.27	15.46 *(c)*	0.64
TA	65.59 *(a)*	1.74	99.20 *(b)*	2.40	120.67 *(c)*	3.75
FCD	2.67 *(b)*	0.09	4.34 *(c)*	0.20	1.96 *(a)*	0.14
NO_3-N	107.59 *(a)*	5.57	216.10 *(b)*	12.09	261.85 *(c)*	18.66
NO_2-N	36.53 *(a)*	1.62	47.18 *(a)*	2.90	61.32 *(b)*	12.36
NH_3-N	63.82 *(a)*	2.40	95.75 *(b)*	6.49	68.96 *(a)*	14.55
OP	36.89 *(a)*	1.70	50.85 *(a)*	4.46	85.12 *(b)*	14.24
TP	91.51 *(a)*	6.02	172.30 *(b)*	11.18	305.95 *(c)*	18.79
SO_4^{-2}	12.68 *(a)*	0.57	17.91 *(b)*	0.90	27.74 *(c)*	2.37
DS	3.61 *(a)*	0.21	4.95 *(a)*	0.28	21.85 *(b)*	1.16
Fe	20.30 *(a)*	0.64	25.85 *(b)*	0.92	37.71 *(c)*	2.40
Cl	15.03 *(a)*	0.39	18.20 *(b)*	0.61	30.71 *(c)*	1.70
TC	23.15 *(a)*	2.80	148.72 *(b)*	14.95	492.58 *(c)*	36.57

(0.704) and SO_4^{-2} (0.733). Finally, the highest values of Wilk's λ were retained by OP (0.853), DO (0.862), Vel (0.884), NH_3-N (0.903), NO_2-N (0.924), pH (0.948) and WT (0.985). The above obtained Wilk's λ quotients of parameters have further been distributed into three distinct groups (Fig. 4A) with their average λ values. The group with lowest average lambda values influenced cluster formation the most.

Using univariate representations (boxplots), comparisons were made among three spatial clusters accomplished from 59 sampling sites. However, it is obvious from Wilk's λ grouping that there are three heterogeneous groups of WQ parameters which discriminate among clusters. Therefore, in order to avoid repetition and have a concise discussion, we select one WQ parameter from each group (viz., TH, NO_3-N and NH_3-N) to assess various patterns linked with spatial

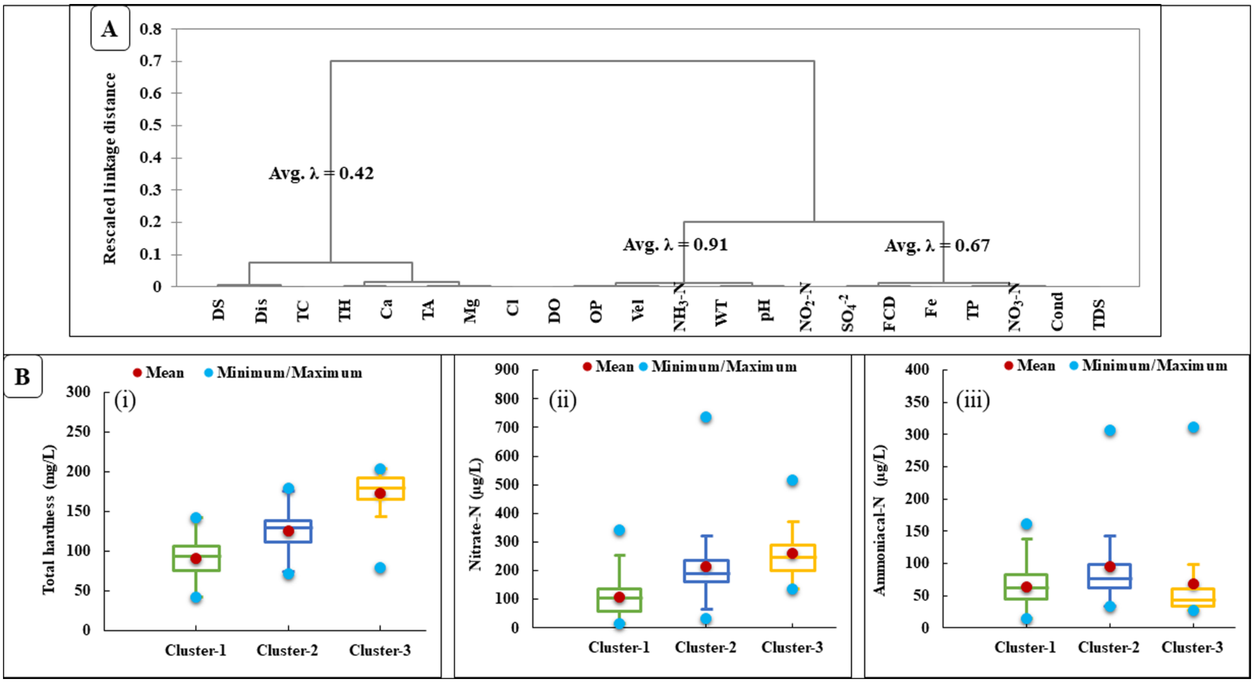

Fig. 4. (A) Dendrogram of spatial Wilk's λ quotients portraying three groups of clusters, (B) Box plots of (i) Total hardness (ii) Nitrate nitrogen and (iii) Ammoniacal nitrogen, related to three spatial clusters.

variations of stream water quality. Mean values of total hardness (Fig. 4B (i)) depict a steady increase from cluster 1 to cluster 3. The increasing inputs of domestic wastes cause hardness in the waters in addition to the natural dissolution of rocks, as we move from headwater to downstream rivers. The mean values of nitrate-nitrogen (Fig. 4B (ii)) were found higher in cluster 3 and cluster 2 which correspond to main river course sites and midstream locations, having influence of high dissolved organic matter loads from settlements and agricultural lands. Although, ammoniacal-nitrogen average values do not differ much among the three clusters (Fig. 4B (iii)) but maximum values in cluster 2 and cluster 3 were observed to be high which may be due to presence of some wastewater inputs causing anaerobic conditions, thus releasing higher amounts of ammonia in waters.

4.3. Temporal variability of WQ parameters and their Wilk's λ

Temporal characteristics of stream WQ were evaluated through CA and ANOVA techniques. CA was accomplished using raw datasets after dividing whole data into four seasons, viz., summer, autumn, winter and spring. It rendered a dendrogram (Fig. 5) producing three distinguishing clusters wherein cluster 1 comprises of autumn and winter seasons, indicating that analysed environmental variables did not vary much during these seasons. Cluster 2 includes spring season and lastly summer period was encompassed in cluster 3. Moreover, ANOVA outcomes revealed that WT of observed samples differs significantly ($p < 0.05$) among the three clusters (Table 3). This is because water temperatures are related to ambient air temperature which remains very low in winters and then increases gradually through spring time and reaches to the maximum level during summers. The current velocity (Vel) of water showed significant variation in three clusters. However, spring season exhibited highest velocity followed by summer and winter months. This is attributed to higher amounts of precipitation during spring time in addition to progressive increase in temperatures which thaws the snow (Mir et al., 2016) and thereby helps in accumulating more water which flows swiftly under the differential gradient of streams. In comparison to spring season (cluster 2), autumn and winter (cluster 1) witnessed significantly lower discharge owing to their lean and freezing periods of water respectively in the basin. Summer time (cluster 3) did not reveal any significant variation in discharge with respect to cluster 1 and 2, thus matching the discharge characteristics with both the seasons. pH of stream water remained alkaline but declined significantly during spring time as compared to other seasons. This may be linked to high rainfall in this season, flushing all the agricultural, domestic and other organic wastes into streams, and results in the formation of acids which upon hydrolysis causes a reduction in pH (Singh et al., 2005). During summers, conductivity and TDS of Jhelum basin streams are considerably higher, followed by winters and are least in spring season. Since summer season is the main activity period in the basin, and as a sequel, huge amounts of municipal and household waste effluents are discharged into stream/river waters and, thus the concentration of dissolved ions (Mir and Gani, 2019) gets enhanced. TH and Ca showed a similar trend wherein both parameters indicated significant variation in spring and summer seasons but vary marginally in winters. Natural sources of hardness in waters are silicate and carbonate rocks (dolomite, gypsum and Panjal volcanics) in the basin, however during summers the higher values of hardness reflect contribution from domestic and agricultural wastes (Mir et al., 2016; Mir and Gani, 2019). Further, total coliform (TC) and other nutrient forms such as NO_2-N, NH_3-N and OP revealed substantial surge in summers which again echoed influence of domestic wastes, untreated sewage, run-off and other agricultural wastes. Particularly, coliform bacterial communities, whose presence makes water unfit for drinking, were found during summers at all study points except 49 (Appendix, Table A1). The reason of their absence at this point was that we collected this sample just where water oozes out from the rock and therefore lacks any contact with animal or human waste which harbours these pathogens. Notably, head water stream points also revealed their occurrence, although in lower numbers, thereby suggesting some amount of animal waste in them. However, as the gradient declines downstream, total coliform increases proportionally due to elevated levels of animal and human wastes. Under the impact of lower temperature in winters, 38% of the sites, mostly upstream, were observed free of coliform thereby indicating slow growth rate at lower temperatures (Jan et al., 2016).

For each sampling season, Wilk's λ quotients were determined for every WQ parameter to ascertain the temporal cluster pattern. The

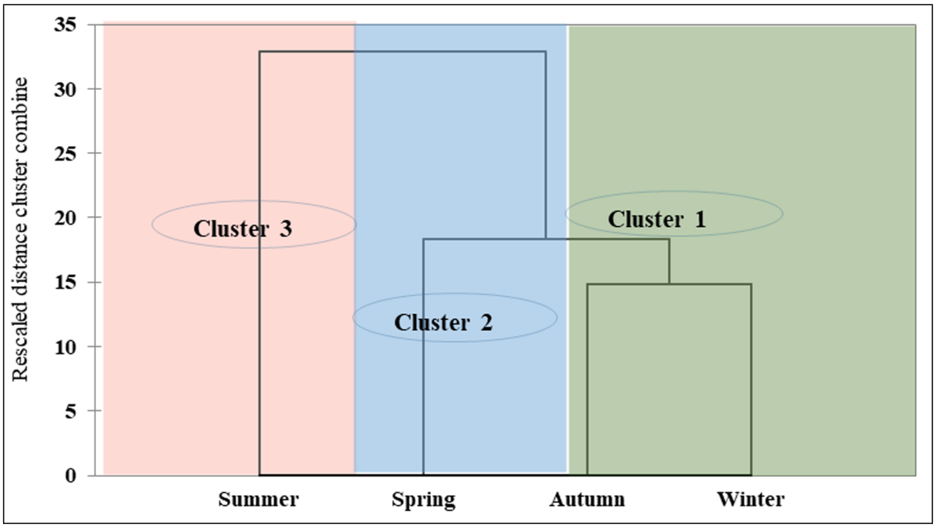

Fig. 5. Dendrogram of seasonal (temporal) cluster analysis illustrating the three clusters.

Table 3

Clusters of monitoring periods (seasons) showing mean values with standard errors (S.E) and ANOVA for WQ parameters. Different letters (italic) indicate statistical difference at $P < 0.05$ among clusters with Tukey's HSD test.

Parameters	Cluster 1		Cluster 2		Cluster 3	
	Mean	S.E	Mean	S.E	Mean	S.E
WT	5.33 *(a)*	0.16	7.75 *(b)*	0.24	16.86 *(c)*	0.58
Vel	0.77 *(a)*	0.04	1.18 *(c)*	0.07	0.96 *(b)*	0.05
Dis	21.36 *(a)*	3.81	39.97 *(b)*	6.84	30.24 *(ab)*	5.83
pH	8.09 *(b)*	0.04	7.93 *(a)*	0.04	8.15 *(b)*	0.04
Cond	208.51 *(b)*	10.09	157.00 *(a)*	13.38	276.46 *(c)*	17.80
DO	7.98 *(a)*	0.15	8.87 *(a)*	0.86	8.65 *(a)*	0.27
TDS	148.71 *(b)*	7.35	103.24 *(a)*	8.01	196.32 *(c)*	12.62
TH	111.74 *(ab)*	3.27	103.75 *(a)*	4.64	117.53 *(b)*	3.77
Ca	28.05 *(ab)*	0.85	26.90 *(a)*	1.22	30.58 *(b)*	0.85
Mg	10.20 *(a)*	0.34	9.27 *(a)*	0.42	10.11 *(a)*	0.43
TA	83.83 *(a)*	2.79	78.78 *(a)*	3.70	83.90 *(a)*	3.23
FCD	3.45 *(b)*	0.16	3.29 *(b)*	0.23	2.46 *(a)*	0.11
NO_3-N	158.88 *(a)*	9.38	155.17 *(a)*	13.44	167.32 *(a)*	14.06
NO_2-N	41.63 *(a)*	2.70	30.77 *(a)*	2.50	56.62 *(b)*	4.03
NH_3-N	65.32 *(a)*	2.71	56.74 *(a)*	3.03	113.29 *(b)*	9.11
OP	40.36 *(a)*	2.88	38.44 *(a)*	2.79	66.93 *(b)*	6.91
TP	136.15 *(a)*	9.69	134.43 *(a)*	13.04	156.07 *(a)*	15.00
SO_4^{-2}	17.34 *(b)*	0.82	16.96 *(b)*	1.13	12.31 *(a)*	1.12
DS	6.15 *(a)*	0.58	6.89 *(a)*	0.72	4.50 *(a)*	0.81
Fe	24.69 *(b)*	0.85	26.56 *(b)*	1.27	19.86 *(a)*	1.25
Cl	15.48 *(a)*	0.61	21.76 *(b)*	0.75	18.07 *(a)*	0.95
TC	91.01 *(a)*	13.09	74.02 *(a)*	17.23	197.80 *(b)*	29.40

average λ values are shown in Fig. 6A, which evidently portray the dominant role of WT (λ = 0.24) in forming the clusters temporally. As mentioned above, four seasons are recognised in Jhelum basin with an apparent temperature differentiation and, accordingly, influence the stream water temperature with time. The second group of parameters with an assigned average λ value of 0.85 includes NH_3-N, Cond, TDS, Vel and Cl. Except velocity, which had a seeming seasonal effect, other variables (NH_3-N, Cond, TDS and Cl) are associated with ingress of untreated sewage, run-off and domestic and agricultural wastes during high anthropo-activity season, and thus produce some differences amid seasons. The less determining role behind other parameters could be their steady presence in stream waters.

Further, assessment of temporal clusters were acquired through univariate plots (boxplots) using three variables (WT, TDS and pH), representing each averaged Wilk's λ group. Highest mean temperatures are witnessed in summers, followed by spring season and minimum mean temperatures existed during autumn and winter periods (Fig. 6B (i)). These trends exactly correspond to the above three clusters generated through CA. The maximum mean TDS is accounted in summer time due to excess inputs from human related activities (Fig. 6B (ii)). Moderate fluctuations of TDS occurred during autumn and winter periods, which could be attributed to lean water flow of tributaries wherein dissolved ions get reasonably increased. Spring season marks a high flow period in streams and, therefore, recorded a minimum TDS due to dilution effect (Mir et al., 2016). Although, pH did not account for much of the variation (Fig. 6B (iii)) but, during winters, it swings more, possibly due to some point source pollutants and also the season corresponds to low water flow period.

4.4. Underlying factors inferring the stream/river water pollution

Understanding the background of hydro-geochemical and ecological processes responsible for the determined WQ cluster patterns required the PCA to be performed on the entire stream water quality dataset. Factor loadings estimated from PCA are considered as strong, moderate and weak with an absolute loading value of > 0.75, between 0.75–0.50 and 0.50–0.30 respectively (Liu et al., 2003). Five varifactor components (VFs), having eigen value > 1 (Vega et al., 1998) and explaining a cumulative variance of 71.92% (Appendix Fig. A), are retained for further analysis (Table 4). The first VF explained 22.66% of the variance, possessing a strong positive varifactor component loadings mainly from Dis, DS and Cl, moderate positive loadings on TC, Fe and SO_4^{-2}. This factor is associated with both natural ionic group salts and anthropogenic contamination sources. The ionic salts in water are produced in the catchments through weathering of carbonates, sulfide minerals (gypsum and pyrites), silicate rocks and springs (Jansen et al., 2010; IMY, 2012). Besides, contribution from other sources like fertilizers and pesticides used in agricultural and horticultural lands, plant matter decomposition, domestic and municipal wastes cannot be ignored (Singh et al., 2013, Varol and Davraz, 2015, Mir et al., 2016). This is elucidated further due to inclusion of total coliform (TC) bacteria in this factor which originates from emptying of untreated sewage drains and open defecation into the stream and river waters. The second VF is responsible for 19.20% of the total variance, with Cond, TDS, TH, Ca, TA and Mg displaying strong and moderate positive loadings

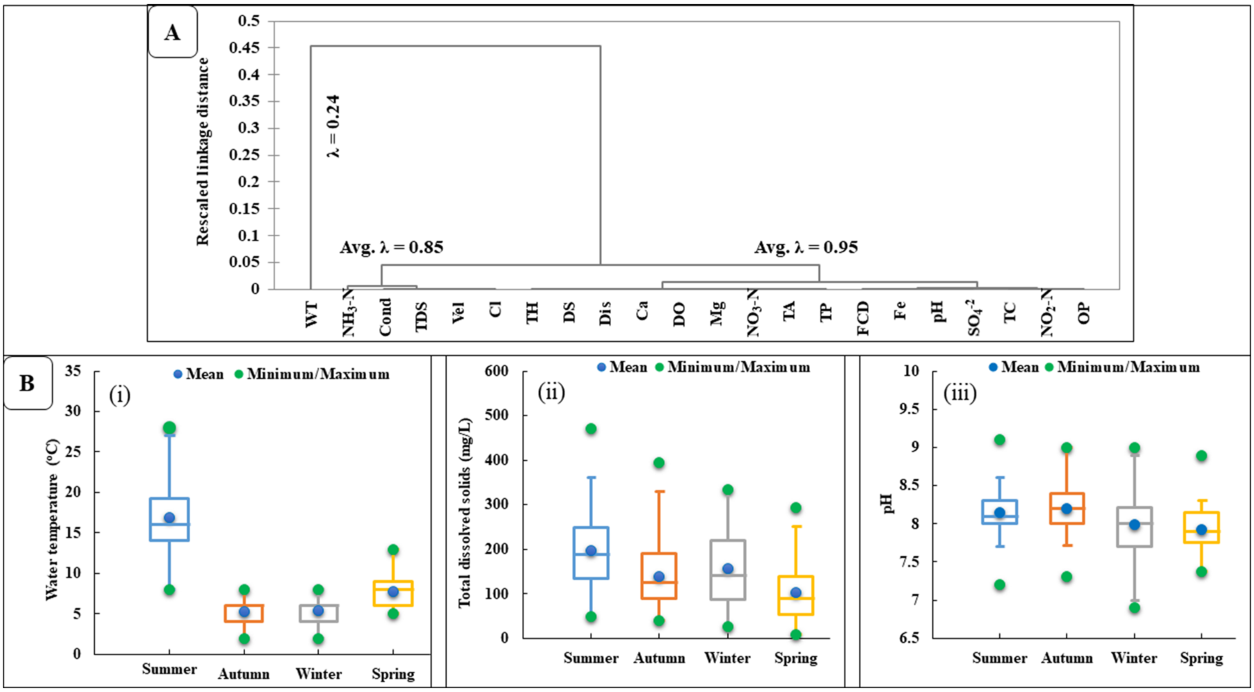

Fig. 6. (A) Dendrogram of seasonal Wilk's λ quotients depicting the three main clusters, (B) Box plots of (i) Water temperature (ii) Total dissolved solids and (iii) pH, for summer, autumn, winter and spring seasons.

Table 4
Loadings of 22 variables on significant principal components (with varimax rotation) for the WQ dataset. Bold and underline values display strong and moderate loadings, respectively.

Variables	VF1	VF2	VF3	VF4	VF5
WT	0.086	0.188	0.601	−0.343	−0.341
Vel	−0.016	−0.091	−0.208	**−0.763**	0.136
Dis	**0.918**	0.105	−0.016	−0.094	−0.057
pH	−0.108	0.016	−0.217	0.16	**−0.787**
Cond	0.02	**0.866**	0.293	0.005	0.086
DO	−0.183	−0.201	−0.053	−0.524	−0.065
TDS	0.011	**0.855**	0.325	0.034	0.072
TH	0.559	**0.734**	0.107	0.208	−0.075
Ca	0.561	**0.705**	0.097	0.149	−0.083
Mg	0.471	0.694	0.083	0.211	−0.053
TA	0.41	**0.753**	0.111	0.268	0.082
FCD	−0.303	0.432	−0.233	0.39	0.416
NO_3-N	0.3	0.198	0.432	0.286	0.296
NO_2-N	−0.009	0.051	**0.714**	0.239	0.033
NH_3-N	−0.194	0.166	**0.803**	−0.011	0.022
OP	0.099	0.168	**0.834**	0.062	0.146
TP	0.405	0.274	0.56	0.168	0.306
SO_4^{-2}	0.634	0.157	−0.125	0.322	0.358
DS	**0.913**	0.117	0.016	0.153	0.014
Fe	0.636	0.045	−0.009	0.225	0.487
Cl	**0.751**	0.261	0.04	−0.117	0.134
TC	0.688	0.312	0.458	0.156	−0.086
Eigen values	4.98	4.23	3.32	1.73	1.57
% of variance	22.66	19.20	15.08	7.87	7.11
Cumulative % variance	22.66	41.86	56.94	64.81	71.92

respectively. This factor alludes to the dominant role of dissolved ions causing hardness and buffering capacity of river waters. Their occurrence is attributed to water-rock interactions in rich carbonate lithology, especially at higher gradients, when fed by glacier and snow melt waters (Mir et al., 2016). The relatively higher concentration of these ions towards downstream river sites reflects additional influx from sand extraction, domestic and agricultural effluents in urbanized dominated areas.

The third VF revealed 15.08% variance with strong positive loadings on NO_2-N, NH_3-N and OP while as loadings of moderate nature are retained by WT and TP. This VF represents the nutrient sources of stream and river water ecosystems in the basin. It is pertinent to mention here that nitrite and ammoniacal forms of nitrogen, in their unionized forms, even at low concentrations, are very toxic to fish (Debels et al., 2005) On the other hand, phosphates have a quick absorption rate in water systems and a high stimulus for eutrophication than nitrogen (Sharpley et al., 2001). The source of these nutrient forms can be domestic and municipal discharges, soil erosion, surface run-off from croplands and contributions from agricultural manure and fertilizers. Previously, water chemistry modifications in river systems have been attributed to land system changes as well as terrace-agricultural practices (Jenkins et al., 1995; France-Landlord et al., 2003; Mello et al., 2018). Massive land system changes in the Jhelum basin are also recognized and, consequently, there is increase in horticultural area while agricultural spatial extents gets reduced (Rashid and Romshoo, 2013; Rather et al., 2016). To suffice the human needs, various types of fertilizers, insecticides, pesticides and fungicides are used frequently in horticultural soils. The upper reaches of tributaries and main Jhelum River encompasses mainly terraced agriculture/horticulture lands for cultivation. Different fertilizers in the form of potash, inorganic nitrogen, phosphorus compounds and farmyard manure are extensively applied in these lands. Due to steep gradients and higher surface runoff, a significant portion is understood to find its way into Jhelum River and its tributaries (Mir et al., 2016). Besides, moderate loadings on WT in this factor specifies the presence of these nutrient forms more in summers because of the high agricultural activities during this season. VF4 described about 7.87% variance and bears strong and moderate negative loadings on Vel and DO respectively. It describes a gradient factor wherein decline of water flow towards downstream river sites, having less slopes, are allied with moderate DO fall due to low

Table 5
Relative weight of WQI parameters.

Parameters	Standards (BIS and EPA, 2012)	Weight (wj)	Rwj
pH	6.5–8.5	3	0.075
TDS	500	4	0.100
T-hardness	300	3	0.075
T-alkalinity	200	3	0.075
Nitrite-N	1	5	0.125
Phosphate	1.5	5	0.125
Sulphate	200	4	0.100
Iron	0.3	5	0.125
Chloride	250	3	0.075
Total coliform	50	5	0.125
		Σ wj = 40	ΣWj = 1

turbulence of waters that diminishes diffusion of gases. In addition, organic matter decomposition in these waters also reduces DO and, thus, it is vital to maintain oxygen in downstream sites for ensuring healthy aquatic life. Finally, VF5 defining 7.11% of total variance, holds strong negative loadings on pH. This VF refers to significant decrease of pH downwards along the main river points because of hydrolysis of acidic material accrued from decaying of raw drainage wastewater.

4.5. Water quality evaluation based on the PCA related WQI

This study assessed the water quality of the Jhelum River and its tributaries for drinking purposes. The Jhelum basin streams/rivers constitute the main source of water for drinking and irrigation in this part of the world. The parameters for establishing WQI were selected using PCA results. The parameters contributing maximum variance ($>$ 0.55 positive/negative) among the five achieved PCs (after varimax rotation) were included for further analysis. It offered 19 variables which still are quite large in number, and, therefore, correlation analysis was applied for their further reduction. Highly correlated parameters, in general, were excluded as they can be gauged from other related variables but some were retained because of their extreme importance (Appendix, Table A2). For example, T-hardness is highly correlated with T-alkalinity and Coliform but all have been incorporated in the assessment due to high significance. Thus, from the initial 22 environmental variables, only 10 parameters are selected for development of WQI.

To calculate the WQI values for each sampling location, the weights were determined for each selected WQ parameter as per their relative importance in the overall water quality for drinking purposes (Table 5). The highest weight of 5 was provided to nitrite-nitrogen, phosphates, iron and coliform bacterial components due to their exceedingly adverse impact on human health. Nitrite form of nitrogen (NO_2-N) constitutes a highly toxic form for both animals and humans (Varol and Davraz, 2015). Likewise, excess amount of phosphates in water causes digestive problems and becomes more harmful (Kumar and Puri, 2012). Water contaminated with coliform bacterial communities causes many health related diseases viz., typhoid, gastroenteritis, diarrhea, and nausea. (Shar et al., 2008). The other stream water quality parameters were allocated weights according to their significance and impacts. Consequently, the relative weights were estimated for all the stream water quality variables (Table 5).

The computed WQI values of all the observed sampling locations varies from 14.95 to 192.43. The WQI distribution map of River Jhelum and its tributaries was prepared in GIS environment and is presented in Fig. 7. The WQ of Jhelum basin streams/rivers ranges in the "excellent" to "poor for drinking" water categories. Thirty-nine (39) sites which constitute about 66% of the total data points are classified as 'excellent' water. It includes all the headwater stream sites, majority of midstream locations and few downstream sites. Stream waters under 'good' category comprises of 14 sites and makes about 24% of the total data locations. This group consist of downstream sites and a few middle stream points. And, finally the main river course sampling sites and a downstream site on Dachigam stream falls under the 'poor' class of water. This group forms about 10% of the sites and remains under serious threat to become unsuitable for drinking if untreated sewage from households along the peripheries, municipal effluents, domestic and animal wastes are not completely interrupted.

The determined effective weights for each stream water quality parameter is statistically summarized in Table 6. These weights were estimated to assess their individual influence towards the WQI. Highest mean effective weights of 39.15% and 26.65% are linked to coliform bacterial communities and pH, respectively, and therefore, are the most effective variables vis-à-vis WQI calculations. It is obvious now that coliform bacterial count and pH are the primary parameters accountable for poor water quality of Jhelum River. TDS, hardness and alkalinity are other parameters that contributes to the WQI. The highest relative values but small mean effective weights retained by nutrients could be primarily because of their low concentrations in samples. These findings are vital for river/stream managers and policymakers and should guide them for maintaining excellent water quality class of WQI throughout the basin by preventing the ingress of domestic sewage, other contaminants and organic matter accumulation.

5. Conclusions

This study assessed the hydro-geochemical patterns and water quality evaluation of the Jhelum River Basin. In this region, spatio-temporal geochemistry of waters is mainly influenced by organic and inorganic pollutants from anthropogenic driven activities and geogenic ionic salts, particularly towards downstream. From the WQI perspective, most of sites (66%) from upstream and midstream regions retained excellent class whilst 24% of sites which includes downstream and few midstream points exhibited good category. However, main river course sites constituting 10%, were of poor class water quality. Primarily, coliform bacteria and pH were responsible for this poor WQ as supported from effective weight contribution of these parameters to WQI. Therefore, chemical attributes towards downstream segments of main River poses safety apprehensions for drinking water purpose when compared to BIS and EPA standards of water quality. This could be ameliorated by cessation of direct inflow of untreated sewage from households, municipal effluents, domestic and animal wastes along the river peripheries. Such type of understanding would therefore provide a scientific basis to river managers for ruminating over the severe consequences of future water quality.

Ethics approval and consent to participate

Research ethics stand adhered while submitting the manuscript

Authors contribution

The study was carried out under the overall supervision and mentorship of Sami Ullah Bhat. All authors contributed with ideas for design, field and lab analysis. Shabir A. Khanday, Sheikh Tajamul Islam and Inam Sabha contributed equally in field work and lab analysis. First author wrote initial draft of manuscript and performed statistical analysis, followed by a review which is completed by second author. Later on, all authors discussed comments jointly and improved the manuscript quality before final submission.

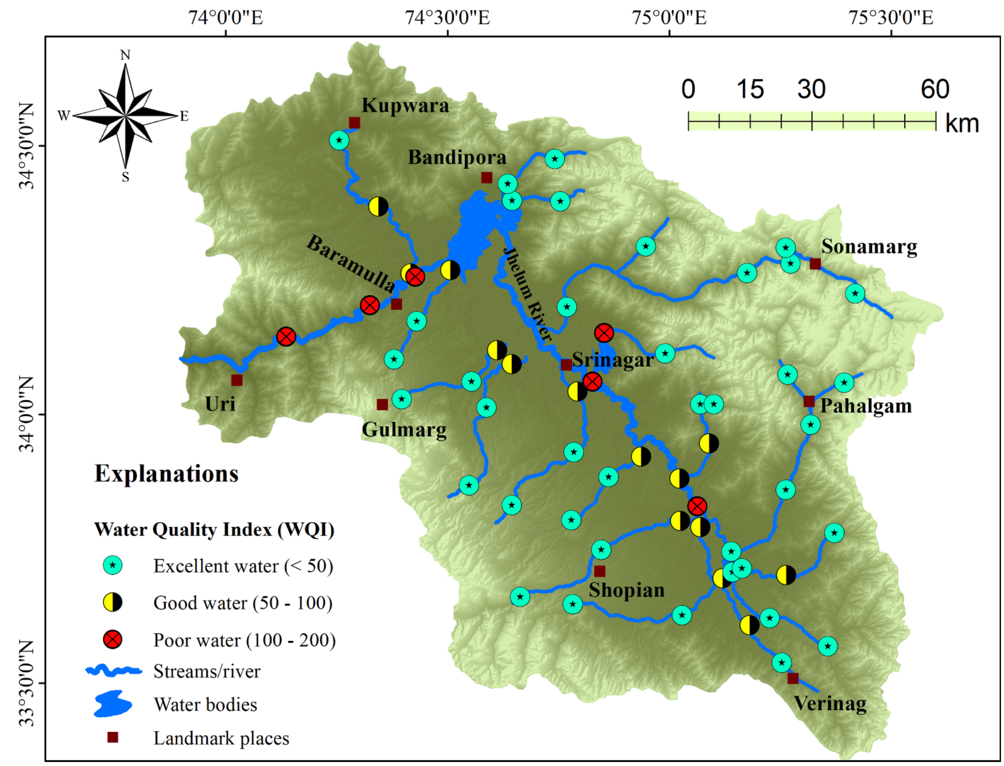

Fig. 7. Water quality index (WQI) distribution map showing excellent, good and poor categories of water in the Jhelum River Basin.

Table 6
Descriptive statistics of the effective weight.

Parameters	Relative weight (Wj)	Effective weight (%)			
		Minimum	Maximum	Mean	S.D.
pH	7.5	4.20	53.53	26.65	14.73
TDS	10.0	2.31	23.13	8.09	3.90
T-hardness	7.5	2.44	15.17	8.07	3.59
T-alkalinity	7.5	2.42	14.95	8.75	3.44
Nitrite-N	12.5	0.24	3.29	1.57	0.79
Phosphate	12.5	0.25	2.07	1.06	0.47
Sulphate	10.0	0.20	5.44	2.19	1.08
Iron	12.5	0.79	6.74	2.91	1.52
Chloride	7.5	0.34	3.22	1.56	0.75
Total coliform	12.5	0.00	85.70	39.15	27.10

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2020.104853.

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