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Assessment and Prediction of Water Quality in an Indian Himalayan River Using Weighted Arithmetic Water Quality Index and Linear Regression Model

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Abstract: Water quality in the Indian Himalayan Region is a pressing concern due to increasing pollution from anthropogenic activities. This study focuses on the analysis and forecast of water quality for a river in this region using the Weighted Arithmetic Water Quality Index (WAWQI) and a linear regression model. Physicochemical parameters including pH, BOD, COD, TDS, and others were measured monthly from 2018 to 2022. The WAWQI is used to assess the water quality, with values indicating a decline over the period. Linear regression analysis is employed to forecast future trends, revealing significant relationships between parameters and water quality deterioration. The study highlights the need for improved wastewater management and pollution control measures to protect these vital water resources. The findings provide critical insights for policymakers and stakeholders to implement effective water quality management strategies in the Indian Himalayan Region.

Keywords: Water Quality • Indian Himalayan Region • Himalayan Rivers • Linear Regression

Introduction

Water is a vital resource for sustaining life and promoting economic and social development. Despite its importance, water quality is under severe threat due to various anthropogenic activities. India is a country with a unique place in the world due to historical, geographical, religious, political, and socio-cultural reasons. (Aggarwal et al 2016) India faces significant challenges in water management. The water demand has been increasing, sewage facilities are often inadequate, and wastewater treatment facilities are scarce, leading to severe impacts on water resources, the environment, and ecology (Khwakaram et al 2012).

Water quality degradation has emerged as a pressing global issue. The United Nations has set an ambitious target to halve the amount of untreated wastewater by 2030. By 2022, 58% of domestic wastewater was being safely treated, yet significant gaps remain, particularly in monitoring and managing industrial wastewater. Despite these challenges, a 2022 evaluation found that 61% of assessed water bodies across 97 countries demonstrated good ambient water quality. Agriculture and untreated wastewater are primary contributors to water quality deterioration, with nitrogen and phosphorus levels frequently exceeding acceptable limits. Addressing these issues requires the adoption of improved agricultural practices and advancements in wastewater treatment, especially in rapidly urbanizing regions (Ross 2023).

Organized outdoor bathing, a widespread cultural practice, underscores the need for water quality standards for both drinking and bathing purposes (Semwal & Akolkar 2006). The safe use of river water is a critical concern, as its quality is determined by its physical, chemical, and biological attributes (Allee & Johnson 1999). These parameters are vital for assessing water pollution and its implications for human health and environmental sustainability. Effective management of water quality is essential to combat threats like biodiversity loss, adverse human health impacts, and challenges to economic and sustainable progress (Kamble et al. 2012; Hirani & Dimble 2019).

The Himalayas, often referred to as the "cryosphere pole of the world," are integral to India's water resource system. Home to major river basins such as the Indus, Ganges, and Brahmaputra, the Himalayan region also includes numerous streams and tributaries, contributing significantly to India's water resources. The region's rivers face numerous challenges, including pollution caused by shifting sediment balances, land use changes, inadequate drainage systems, and the disposal of untreated wastewater (Rafiq et al. 2016; Aithani et al. 2021; Seth et al. 2014). Spring water quality heavily influences the water quality of Himalayan rivers. Studies in Uttarakhand, for instance, have highlighted elevated levels of total hardness, alkalinity, chloride, sodium, and potassium in the Gola River. Seasonal variations in dissolved oxygen, alkalinity, and chloride have also been observed in the Kosi River in Almora (Chhimwal et al. 2022). Groundwater and surface water in the Kumaon and Garhwal regions are often contaminated due to geological factors, industrial discharge, and developmental activities (Dimri et al. 2021; Seth et al. 2014).

To simplify and communicate water quality data effectively, indices such as the Water Quality Index (WQI) and the Weighted Arithmetic Water Quality Index (WAWQI) have been developed. These tools integrate multiple water quality parameters into a single composite score, providing a concise representation of water quality. The WAWQI is particularly useful for stakeholders as it offers actionable insights into water quality management (Abbasi & Abbasi 2012; Chandra et al. 2017).

The Suswa River in Dehradun, Uttarakhand, exemplifies the challenges of maintaining water quality in urban and rural areas. Identified as a polluted stretch by the Central Pollution Control Board (CPCB) in 2018, the river receives substantial municipal and rural waste. Urban drainage systems, including the Rispana and Bindal rivers, contribute millions of liters of untreated wastewater daily. Effluents from 51 drains, including the Song River, exacerbate pollution levels (CPCB 2018; Rawat et al. 2019). To address these issues, the Uttarakhand River Rejuvenation Committee launched a program in 2018, establishing water quality monitoring sites along the Suswa River. The program employs the WAWQI for assessing river water quality, combining physicochemical parameters to provide a comprehensive evaluation. This approach highlights areas requiring immediate intervention (Patel 2023).

Linear regression (LR) has proven to be an effective tool for predicting water quality trends due to its ability to establish clear relationships between predictive variables and outcomes. By analyzing physicochemical parameters, LR facilitates the understanding of how pollution sources impact water quality. Its simplicity and efficiency make it particularly valuable in scenarios with limited data, enabling informed decision-making for water resource management (Shrestha & Kazama 2006; Khan & Umar 2024; Chen et al. 2019; Maulud & Abdulazeez 2020).

The degradation of water quality poses existential threats, including biodiversity loss and compromised human health. Addressing these issues requires a multi-faceted approach that includes enhancing wastewater treatment facilities to handle industrial and agricultural waste effectively, adopting sustainable agricultural methods to minimize nutrient runoff into water bodies, implementing robust monitoring systems and enforcing strict

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pollution control regulations, engaging local communities in water conservation and pollution prevention efforts. By integrating scientific tools like WQI and LR with proactive policy measures, stakeholders can ensure sustainable water resource management and safeguard environmental and public health outcomes.

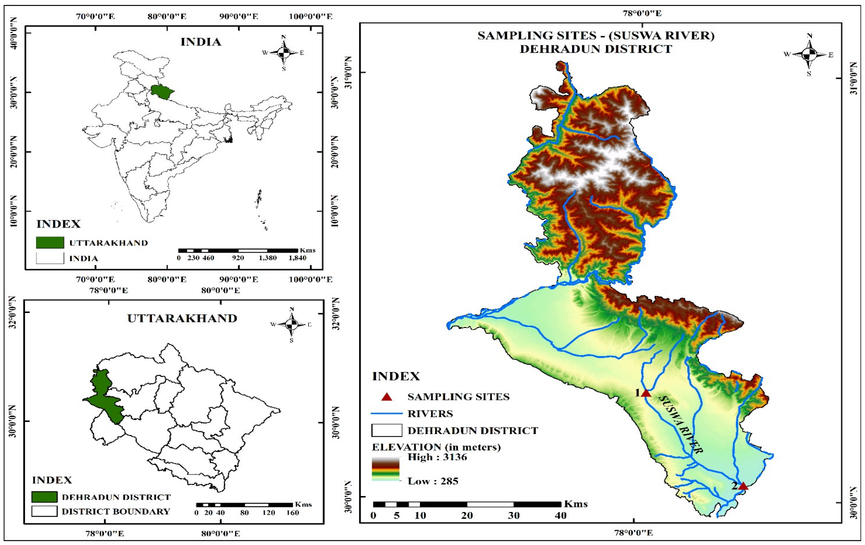

Figure 1. Sampling Sites for Water Quality Monitoring in Dehradun District

Methodology

Water Quality Data of 11 parameters viz. pH, Biological BOD mg.l^{-1}, COD mg.l^{-1}, Temp °C, DO mg.l^{-1}, Alkalinity $CaCO_3$ mg.l^{-1}, Chlorides mg.l^{-1}, Calcium as Cl mg.l^{-1}, Magnesium as Mg mg.l^{-1}, Hardness as $CaCO_3$ mg.l^{-1}, TDS mg.l^{-1} for all months of 2017 to 2022 is collected from Uttarakhand Pollution Control Board for two stations

The National Sanitation Foundation (NSF) developed and provides support for the Water Quality Index. The symbol for this water quality index is: -

$$WQI = \sum_{i=1}^{p} WiQi$$

where p denotes the i^{th} parameter measured values, the quality rating is denoted by Qi, and the relative weight of the i^{th} parameters is denoted by Wi.

The water quality index arithmetic index is a very popular and standard method used by many researchers in their studies. In this study, the quality rating can be calculated using the following equation:

$$Q_i = \left\{\frac{V_{actual} - V_{ideal}}{V_{standard} - V_{ideal}}\right\} \times 100$$

where Qi represents the i_{th} parameter's quality rating out of n water quality parameters. Vactual represents the actual and definite value of the quality parameters, V_{ideal} represents the parameters' ideal value, and $V_{standard}$ represents the recommended standard value of the parameters by WHO, BIS, etc.

The ideal values for DO and pH are 14.6 and 7 mg.l-1, whereas for the other parameters, it is equal to zero.

After calculating the quality rating (relative weight), Wi is calculated by inverting the parameter's standard value. Finally, the overall water quality index (WQI) was calculated using the equation below:

$$WQI = \sum WiQi / \sum Wi$$

Here, Wi and Qi stand for the relative weight and quality rating, respectively.

Forecast (Trend Analysis)

In this study, the linear regression model has been utilized to forecast the pollution trend

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analysis. According to the linear regression model, the relationship between the two variables a and b can be expressed as:

$$B = x + yA + e$$

Where x and y are the model parameters, which are known as regression coefficients, and B is the dependent variable. A is known as an independent variable, and e is the error variable. Making a prediction using a linear regression model is

$$B = x + yA$$

Table 1. The Standard Values for Water Quality Index (WQI) using the Weight Arithmetic Water Quality Index Method

WQI Value	Rating of Water Quality	Grading
0-25	Excellent Water Quality	A
26-50	Good Water Quality	B
51-75	Poor Water Quality	C
76-100	Very Poor Water Quality	D
Above 100	Unsuitable for Drinking Purposes	E

Source: Brown, R. M. et al., 1972

Forecast (Trend Analysis)

In this study, the linear regression model has been utilized to forecast the pollution trend analysis. According to the linear regression model, the relationship between the two variables a and b can be expressed as:

$$B = x + yA + e$$

Where x and y are the model parameters, which are known as regression coefficients, and B is the dependent variable. A is known as an independent variable, and e is the error variable. Making a prediction using a linear regression model is

$$B = x + yA$$

The following equations are used to calculate the parameters x and y.

$$x = \frac{\sum a^2 \sum b - \sum a \sum ab}{n \sum a^2 - (\sum a)\hat{2}}$$

$$y = \frac{n \sum ab - \sum a \sum b}{n \sum a^2 - (\sum a)\hat{2}}$$

Results

Parameters Considered for Water Quality Index

Table 02 provides a detailed overview of the water quality parameters measured at Site 01 from 2018 to 2022. The pH levels show a slight decline over the years, with values ranging from 7.88 in 2018 to 7.06 in 2022, indicating increasing acidity. BOD and COD both exhibit a decreasing trend, with BOD dropping from 33.17 mg.l-1 in 2018 to 21.25 mg.l-1 in 2022 and COD decreasing from 134.00 mg.l-1 to 86.33 mg.l-1 over the same period, suggesting improving organic pollution levels.

The temperature of the water fluctuated, peaking at 22.27°C in 2021 and dropping to 19.25°C in 2022. DO levels varied, with an increase in 2020 to 5.72 mg.l-1, followed by fluctuations, ending at 3.83 mg.l-1 in 2022. Alkalinity as CaCO3 showed variations, with a significant increase in 2021 to 338.08 $mg.l^{-1}$, then a decrease to 263.50 $mg.l^{-1}$ in 2022. Chloride levels generally increased, peaking at 38.50 $mg.l^{-1}$ in 2021 before reducing to 32.08 $mg.l^{-1}$ in 2022. Calcium content saw a notable rise in 2021 to 303.83 mg.l-1, before decreasing to 255.58$mg.l^{-1}$ in 2022. Magnesium levels declined from 130.00$mg.l^{-1}$ in 2018 to 71.00 $mg.l^{-1}$ in 2022. Total hardness as CaCO3 and Total Dissolved Solids (TDS) showed similar trends, with peaks in 2021 followed by declines, ending at 320.50 $mg.l^{-1}$ and 335.08 $mg.l^{-1}$ respectively in 2022. This data highlights fluctuations and overall trends in the water quality of the site over the five-year period.

Table 2. Value of the Various Parameters of Water Quality at Site 01 (2018-2022)

Parameters	Years				
	2018	2019	2020	2021	2022
pH	7.88	7.76	7.75	7.59	7.06
BODmg.l^{-1}	33.17	24.92	25.42	25.75	21.25
CODmg.l^{-1}	134.00	106.67	101.83	91.50	86.33
Temp °C	18.75	19.50	20.43	22.27	19.25
DO mg.l^{-1}	2.42	3.33	5.72	3.22	3.83
Alkalinity CaCO3 mg.l^{-1}	293.50	255.83	313.92	338.08	263.50
Chlorides mg.l^{-1}	32.33	25.17	30.63	38.50	32.08
Calcium as Cl mg.l^{-1}	218.83	200.00	199.58	303.83	255.58
Magnesium as Mg mg.l^{-1}	130.00	100.00	108.17	71.08	71.00
Hardness as CaCO3 mg.l^{-1}	348.83	300.00	307.75	374.92	320.50
TDS mg.l^{-1}	422.83	361.25	439.92	441.33	335.08

Table 3. Value of the Various Parameters of Water Quality at Site 02 (2018-2022)

Parameters	***Years***				
	2018	***2019***	***2020***	***2021***	***2022***
pH	7.68	7.90	7.89	7.84	7.75
BOD mg/l	1.05	1.03	1.23	1.45	1.43
COD mg/l	5.67	5.67	5.83	5.83	5.80
Temp °C	18.83	19.58	21.17	21.14	19.83
DO mg/l	8.87	9.15	9.40	9.30	9.23
Alkalinity CaCO3 mg/L	82.50	80.17	138.58	154.83	171.25
Chlorides mg/L	7.17	8.17	11.13	11.00	9.17
Calcium as Cl mg/L	53.33	49.42	94.42	137.50	169.42
Magnesium as Mg mg/L	40.50	37.08	55.08	40.67	35.42
Hardness as CaCO3 mg/L	93.83	86.50	144.83	178.17	204.83
TDS mg/L	127.75	159.08	238.42	229.75	222.33

The table 03 presents water quality parameters measured at Site 02 from 2018 to 2022. The pH values remained slightly alkaline throughout the years, ranging from 7.68 in 2018 to 7.75 in 2022, with minor fluctuations. Biochemical Oxygen Demand (BOD) levels showed a slight increase, rising from 1.05 mg/L in 2018 to 1.43 mg/L in 2022, indicating a gradual rise in organic pollutants. Similarly, Chemical Oxygen Demand (COD) exhibited minimal variation, staying within a narrow range of 5.67 mg/L to 5.83 mg/L. Water temperature varied moderately, peaking at 21.17°C in 2020 and decreasing slightly to 19.83°C in 2022. Dissolved Oxygen (DO) levels consistently increased over the years, from 8.87 mg/L in 2018 to 9.23 mg/L in 2022, reflecting improved oxygen availability. Alkalinity, expressed as CaCO3, showed a significant increase, from 82.50 mg/L in 2018 to 171.25 mg/L in 2022, which could suggest rising levels of bicarbonates in the water. Chlorides levels fluctuated slightly, peaking at 11.13 mg/L in 2020 before decreasing to 9.17 mg/L in 2022. Calcium levels showed a notable increase over the years, rising from 53.33 mg/L in 2018 to 169.42 mg/L in 2022. Conversely, magnesium levels varied, peaking in 2020 at 55.08 mg/L and then declining to 35.42 mg/L by 2022. Total hardness, expressed as $CaCO_3$, exhibited a steady increase, climbing from 93.83 mg/L in 2018 to 204.83 mg/L in 2022, reflecting the combined contributions of calcium and magnesium ions. Total Dissolved Solids (TDS) increased significantly from 127.75 mg/L in 2018, peaking at 238.42 mg/L in 2020, and slightly declining to 222.33 mg/L in 2022. These trends provide insights into the variations in water quality parameters at Site 02 over the observed period.

Water Quality Index of Suswa River

Water Quality Index of Site 01

The WQI started at a relatively high value of 331.28 in 2018 but showed a decreasing trend over the following years. In 2019, there was a notable drop to 263.50, indicating a decline in water quality. This downward trend continued in 2020 and 2021, with WQI values of 259.09 and 262.23, respectively. By 2022, the WQI for Site 01 reached its lowest value in the given time frame, dropping further to 209.09. Overall, Site 01 experienced a consistent decrease in water quality over the analyzed period.

For Site 02

Site 02 shows a different trend compared to Site 01. The WQI for Site 02 started lower at 60.62 in 2018 but demonstrated a slight increase in subsequent years. By 2019, the WQI rose to 67.44, indicating an improvement in water quality compared to the previous year.

This positive trend continued in 2020 and 2021, with WQI values of 71.36 and 71.75, respectively, suggesting further enhancements in water quality. However, in 2022, there was a slight decrease in WQI to 68.80, but the overall trend for Site 02 remained relatively stable and showed improvement over the analyzed period.

The provided equations represent linear regression models, each with an associated coefficient of determination (R^2) indicating the goodness of fit:

$y = -24.565x + 49886$ with $R^2 = 0.7978$

$y = 2.0683x - 4109.9$ with $R^2 = 0.5295$

Table 4. Water Quality Index of Suswa River

Year	Water Quality Index of Suswa River	
	Site 01	Site 02
2018	331.28	60.62
2019	263.50	67.44
2020	259.09	71.36
2021	262.23	71.75
2022	209.09	68.80

In the first equation, the dependent variable y is determined by the independent variable x through the formula $y = -24.565x + 49886$. This equation suggests that for every unit increase in x, y is expected to decrease by 24.565 units, starting from an initial value of 49886. The coefficient of determination R^2 indicates that approximately 79.78\% of the variability in y can be explained by the variability in x using this linear model. In the second equation, the dependent variable y is determined by the independent variable x through the formula $y = 2.0683x - 4109.9$. Here, for every unit increase in x, y is expected to increase by 2.0683 units, starting from an initial value of -4109.9. The coefficient of determination R^2 indicates that approximately 52.95\% of the variability in y can be explained by the variability in x using this linear model. These equations serve as mathematical representations of relationships between variables, allowing for predictions and analysis within their respective contexts. The higher the R^2 value, the better the model fits the data, indicating a stronger relationship between the variables.

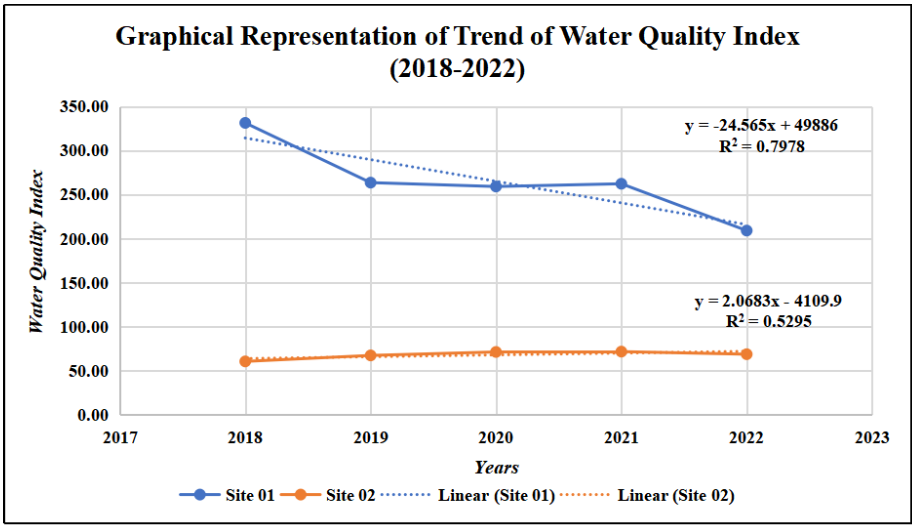

Figure 2. Graphical Representation of Trend of Water Quality Index (2018-2022)

The provided data in Table No. 05 represents the Water Quality Index (WQI) calculated using the monthly mean values of various physicochemical parameters at Site 01 over five years from 2018 to 2022. Overall, the WQI fluctuates throughout the years, indicating variability in water quality. In 2018, the WQI ranges from 52.92 (in March) to 361.5 (in February), showing a wide range of variation. There's a significant improvement in water quality in 2019 compared to 2018, with the WQI generally lower across all months. The trend continues in 2020, with further improvements seen in the first half of the year, followed by some fluctuations in the second half. However, in 2021, there's a noticeable increase in the WQI compared to 2020, indicating a decline in water quality. The trend of decreasing water quality appears to continue into 2022, with generally lower WQI values across all months compared to 2021. It's also essential to identify any specific trends or patterns within each year. In 2018, there were periods of both high and low water quality, with significant fluctuations observed from month to month. In 2019, there's a more consistent pattern of improvement, with generally lower WQI values indicating better water quality throughout the year. 2020 shows a mix of improvements and fluctuations, with some months experiencing better water quality than others. 2021 stands out as a year with a noticeable decline in water quality, especially in the latter half of the year, as indicated by higher WQI values. 2022 continues the trend of decreasing water quality, with lower WQI values observed across most months compared to 2021.

Correlation Table for Physicochemical Parameters at Site 01

The correlation table (Table 6) shows the relationship between different physicochemical parameters measured at Site 01 monthly from 2018 to 2022. Each cell in the table represents the correlation coefficient between two parameters. The correlation coefficient ranges from -1 to 1, where: ‘1’ indicates a perfect positive correlation, ‘-1’ indicates a perfect negative correlation, and ‘0’ indicates no correlation.

Table 5. WQI Prepared Using the Monthly Mean Values of Physicochemical Parameters Site 01 (2018- 2022)

Months	Years				
	2018	2019	2020	2021	2022
Jan	330.01	281.1	207.1	276.78	240.2

Feb	361.5	290.32	306.08	250.1	216.73
Mar	337.12	52.92	281.27	288.96	233.66
Apr	350.85	289.29	58.628	256.04	212.18
May	321.53	305.19	309.02	245.28	224.24
June	334.21	283.01	234.67	274.69	228.07
July	314.22	272.33	296.6	299.13	230.81
Aug	327.56	251.8	310.22	233.46	190.27
Sept	312.38	245.66	286.95	257.93	227.62
Oct	332.17	299.15	295.01	245.49	173.47
Nov	334.33	285.87	272.31	282.89	156.52
Dec	319.5	305.36	251.22	235.96	175.33

pH shows a positive correlation with BOD mg.l^{-1} (0.372571), COD mg.l^{-1} (0.327176), and TDS mg.l^{-1} (0.099683). It has a negative correlation with Chloride mg.l-1 (-0.12654) and Temp ℃ (-0.07011). BOD mg.l^{-1} has a significant positive correlation with COD mg.l^{-1} (0.91452), and moderate positive correlations with Alkalinity $CaCO_3$ mg.l^{-1} (0.488283) and Hardness as CaCO3 mg.l^{-1} (0.556731). COD mg.l^{-1} shows a significant positive correlation with BOD mg.l^{-1} (0.91452) and moderate positive correlations with Alkalinity $CaCO_3$ mg.l^{-1}(0.380713) and Hardness as CaCO3 mg.l^{-1} (0.464091). Temp ℃ has negative correlations with DO mg.l^{-1} (-0.43574), Alkalinity CaCO3 mg.l^{-1} (0.246672), and TDS mg.l^{-1} (0.126503). DO mg.l^{-1} shows a negative correlation with BOD mg.l^{-1} (-0.35912) and COD mg.l^{-1} (-0.32546) and a positive correlation with Temp ℃ (0.43574). Alkalinity CaCO3 mg.l^{-1} has positive correlations with BOD mg.l^{-1} (0.488283), COD mg.l^{-1} (0.380713), and Hardness as CaCO3 mg.l^{-1} (0.691692). Chlorides mg.l^{-1} has a moderate positive correlation with Alkalinity CaCO3 mg.l^{-1} (0.576001). Calcium as Cl mg.l^{-1} has a moderate positive correlation with Alkalinity CaCO3 mg.l^{-1} (0.727317) and Hardness as CaCO3 mg.l^{-1} (0.814731). Magnesium as Mg mg.l^{-1} shows a moderate positive correlation with Alkalinity CaCO3 mg.l^{-1} (0.157002). Hardness as CaCO3 mg.l^{-1} has moderate positive correlations with BOD mg.l^{-1} (0.556731), COD mg.l^{-1} (0.464091), Alkalinity CaCO3 mg.l^{-1} (0.691692), and Calcium as Cl mg.l^{-1} (0.814731). TDS mg.l^{-1} has a moderate positive correlation with Alkalinity CaCO3 mg.l^{-1} (0.667427) and Hardness as CaCO3 mg.l^{-1} (0.520516).

Linear Trend (Forecast) of Water Quality Index (2018-2027)

The diagram illustrates the linear trend forecast of the Water Quality Index (WQI) for two different sites, Site 01 and Site 02, over a period from 2018 to 2027. The WQI is an aggregate measure used to evaluate the overall quality of water, where a lower WQI value signifies better water quality. This graph provides insights into historical data (2018-2022) and projects future trends (2023-2027) for both sites.

Analysis of Site 01

Site 01 is represented by the blue line. The historical data points show a notable decline in WQI from 2018 to 2022. The trend line equation for Site 01 is given as y=−24.565x+49886y = -24.565x + 49886y=−24.565x+49886 with an R^2 value of 0.7978. The negative slope of -24.565 indicates a consistent decrease in the WQI over time, suggesting an improvement in water quality at Site 01. The R^2 value of 0.7978 implies a strong correlation between the historical data and the linear model, indicating that about 79.78% of the variability in WQI can be explained by this model.

Table 6. Correlation Table for Physico chemical Parameters at Site 01 (Monthly Data from 2018-2022)

Parameters	pH	BOD $mg.l^{-1}$	COD $mg.l^{-1}$	Temp °C	DO $mg.l^{-1}$	Alkalinity CaCO3 $mg.l^{-1}$	Chlorides $mg.l^{-1}$	Calcium as Cl $mg.l^{-1}$	Magnesium as Mg $mg.l^{-1}$	Hardness as CaCO3 $mg.l^{-1}$	TDS$mg.l^{-1}$
pH	1	0.372571	0.327176	-0.07011	0.051101	-0.00157	-0.12654	-0.18529	0.214379	-0.00853	0.099683
BOD $mg.l^{-1}$	0.372571	1	0.91452	-0.04908	-0.35912	0.488283	0.414338	0.288771	0.490871	0.556731	0.427849
COD$mg.l^{-1}$	0.327176	0.91452	1	-0.13723	-0.32546	0.380713	0.26559	0.168	0.523958	0.464091	0.354529
Temp °C	-0.07011	-0.04908	-0.13723	1	-0.43574	0.246672	0.15195	0.234853	-0.35037	-0.00426	0.126503
DO $mg.l^{-1}$	0.051101	-0.35912	-0.32546	-0.43574	1	-0.28191	-0.29143	-0.27532	-0.07284	-0.29294	-0.19352
Alkalinity CaCO3 $mg.l^{-1}$	-0.00157	0.488283	0.380713	0.246672	-0.28191	1	0.576001	0.661373	0.157002	0.691692	0.667427
Chlorides $mg.l^{-1}$	-0.12654	0.414338	0.26559	0.15195	-0.29143	0.576001	1	0.727317	-0.06355	0.612419	0.604821
Calcium as Cl $mg.l^{-1}$	-0.18529	0.288771	0.168	0.234853	-0.27532	0.661373	0.727317	1	-0.15988	0.814731	0.434616
Magnesium(Mg $mg.l^{-1}$)	0.214379	0.490871	0.523958	-0.35037	-0.07284	0.157002	-0.06355	-0.15988	1	0.427225	0.196076
Hardness (CaCO3 $mg.l^{-1}$)	-0.00853	0.556731	0.464091	-0.00426	-0.29294	0.691692	0.612419	0.814731	0.427225	1	0.520516
TDS $mg.l^{-1}$	0.099683	0.427849	0.354529	0.126503	-0.19352	0.667427	0.604821	0.434616	0.196076	0.520516	1

The declining WQI trend for Site 01 is a positive sign, showing that the water quality has been improving and is expected to continue to do so if current conditions persist. This improvement could be attributed to effective pollution control measures, better management practices, or natural recovery processes. However, continuous monitoring and maintenance of these efforts are crucial to ensure the trend continues.

Analysis of Site 02

Site 02 is represented by the orange line. The historical data for Site 02 from 2018 to 2022 shows relatively stable WQI values with slight fluctuations. The trend line equation for Site 02 is y=2.0683x+4109.9y = 2.0683x + 4109.9y=2.0683x+4109.9 with an R^2 value of 0.5295. The positive slope of 2.0683 suggests a slight increase in WQI over time, indicating a minor deterioration in water quality at Site 02. The R^2 value of 0.5295 signifies a moderate fit of the linear model to the data, explaining about 52.95% of the variability in WQI.

The slight upward trend in WQI at Site 02 suggests that while the water quality has been relatively stable, there might be underlying factors causing a gradual decline. This could be due to increasing pollution sources, ineffective management practices, or other environmental factors. Addressing these issues is essential to prevent further deterioration and to potentially reverse the trend.

Comparative Analysis and Implications

The contrasting trends between Site 01 and Site 02 highlight the differing water quality dynamics at these locations. While Site 01 shows a promising decline in WQI, indicating improving water quality, Site 02 shows a slight increase, indicating a need for intervention to prevent further deterioration. This comparative analysis underscores the importance of site-specific strategies and interventions to manage and improve water quality effectively.

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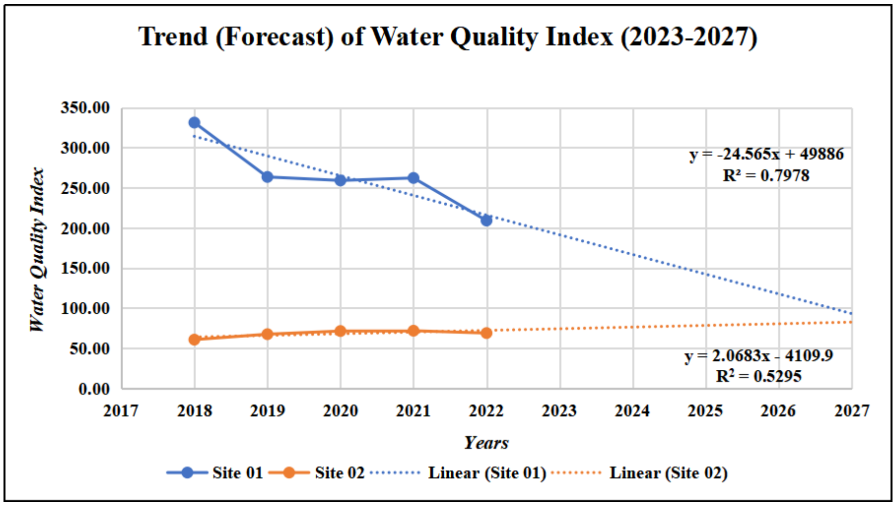

Figure 3. Linear Trend (Forecast) of Water Quality Index (2018-2027)

The linear trend forecasts provide valuable insights for policymakers, environmentalists, and local authorities. For Site 01, maintaining and enhancing current efforts could lead to sustained improvements in water quality. For Site 02, identifying and mitigating pollution sources and implementing effective management practices are critical to reversing the upward trend in WQI.

Conclusion

The study on the Suswa River in the Indian Himalayan region analyzes water quality trends from 2018 to 2022 using the Weighted Arithmetic Water Quality Index (WAWQI) and linear regression models. It reveals significant spatial and temporal variations at two sites. At Site 01, the WAWQI declined notably from 331.28 in 2018 to 209.09 in 2022, reflecting improved water quality due to effective pollution control and management practices. The linear regression model for Site 01 (R^2 = 0.7978) demonstrates a strong fit, explaining 79.78% of the WAWQI variability and emphasizing the success of environmental policies and natural recovery processes.

Conversely, Site 02 exhibited relative stability with minor fluctuations, as WAWQI increased from 60.62 in 2018 to 71.75 in 2021, followed by a slight decrease to 68.80 in 2022. The linear regression model for Site 02 (R^2 = 0.5295) indicates a moderate fit, explaining 52.95% of the variability. This trend suggests potential underlying pollution issues requiring targeted interventions to improve water quality management.

Correlation analysis among physicochemical parameters revealed significant relationships, such as a strong positive correlation between Biochemical Oxygen Demand (BOD) and Chemical Oxygen Demand (COD) and moderate correlations involving BOD, Alkalinity, and Hardness. These insights can guide future monitoring and management strategies.

Forecasting for 2023-2027 projects continued water quality improvement at Site 01 if current conditions persist, while Site 02's slight upward trend in WAWQI indicates a need for proactive measures to prevent further deterioration. The study underscores the necessity for site-specific water management strategies. Policymakers and local authorities must collaborate to implement effective pollution control measures, ensuring the ecological integrity of the Suswa River through continuous monitoring and adaptive management.

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