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Multi-seasonal Water Quality Assessment of a Small Alluvial River Using In-Situ Measurements and Satellite Images

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Abstract: Compared to larger rivers, water quality assessments in small streams are institutionally undertaken less frequently, especially in resource-scarce communities in the Global South. Yet, smaller streams are more sensitive to the ongoing landscape changes within their riparian zone, whose physicochemical signatures may get dampened within the high flows of larger rivers or mixed with similar signals from other parts of the catchment. The Sutunga River in eastern India was thus studied given the intended work's specific focus on smaller rivers. Our objectives were to measure the surface water quality along this small alluvial river situated within agricultural landscapes during the monsoon, post-monsoon, and pre-monsoon periods using a weighted arithmetic-based WQI, to investigate seasonal turbidity, TSS, nitrate (NO_3-N), and chloride (Cl^-) concentrations along the river's course; and to use NDTI to assess its turbidity following prolonged rainfall events and high flows, with field validation. The computed water quality index (WQI) was based on in-situ measurements from monsoon 2023 to pre-monsoon 2024 and the Normalized Difference Turbidity Index (NDTI) derived from Sentinel-2A images in the Google Earth Engine (GEE) platform. There was substantial variability in WQI between the monsoon and post-monsoon periods ($p = 0.001$), but no significant difference was noticed between the post-monsoon and pre-monsoon ($p = 0.184$), with the majority of sites reporting good quality. One-way ANOVA results showed that DO, NO_3-N, Turbidity, and TSS were the key parameters related to water quality, with significant seasonal variations. The polynomial (6^{th} order) line best fit the parameter distributions and a Pearson's correlation matrix highlighted both turbidity and TSS as significantly influencing the surface water quality. The diminishing flow in the post-monsoon and pre-monsoon periods indicate greater stress on the stream habitat environment, with a concomitant increase in nitrate and chloride concentration levels, despite the drop in turbidity and TDS levels from the monsoon period. This variability underlines the importance of conducting site-specific investigations along the river's course to better understand the underlying causes of such seasonal oscillations.

Keywords:
water quality, alluvial river, Google Earth Engine, turbidity, seasonal variations

1. Introduction

Water quality is an important aspect of the lotic system, since it influences the habitats of aquatic species and the overall riparian ecosystem along rivers. In lowland floodplains and mountain foothill zones, small rivers are vital for transporting runoff from their respective catchments to the main trunk stream (Graham et al. 2010; Fryirs and Brierley 2012). Additionally, their ecosystems are sensitive and significantly impacted by their connectivity with the surroundings in vertical, lateral and longitudinal dimensions (Wohl 2012, 2017). Particularly, during the summer monsoon season in the Indian subcontinent, river networks are directly and indirectly linked to every aspect of the surrounding landscape and there is a marked change from their geomorphic (and consequently ecological) character in the non-monsoonal period (Mondal and Patel 2020; Saha et al. 2020). Sustenance and management of the ecosystem services obtained from these small rivers and their own operative functions following the flood cycle, which often relies on their self-organizing systems, requires focused studies on such environments (Brierley and Fryirs 2005; Wohl et al. 2015; Mondal and Patel 2018). However, it is often the larger rivers that are gauged and monitored for their discharge and water quality parameters, particularly in resource-constrained economies in the Global South, and there is scant database on the smaller streams that feed them. Yet, many agricultural societies are dependent on these smaller streams and the specific nature of their water quality alterations during the monsoon to non-monsoon seasons bears investigation to ascertain the related parameter transformations due to rainfall and runoff and also agricultural water use. Further, where integrative river basin management is the usual stated goal of ambitious river rehabilitation programmes like the Namami Gange in India, it is usually the lack of information about the dynamics and health of the smaller tributary rivers that hinders the success of the proposed river rejuvenation schemes (Mondal and Patel 2022).

One of the most crucial components of river health assessment is determining the water quality as it relates to the provision of healthy in-stream aquatic and riparian habitats (Bagchi and Bussa 2011; Boyd 2020). Floodplain river ecosystem management depends on evaluating the health of rivers (Belletti et al. 2015) and facilitating appropriate actions based on their existing situation (Rinaldi et al. 2013; Cornejo-Denman et al. 2018). Water quality assessment forms an integral component of such hydromorphological frameworks (Harman et al. 2012). Additionally, the monitoring and evaluation of water quality in this instance helps to safeguard the aquatic flora and wildlife found in rivers and streams, which is essential to achieving various sustainable development objectives (Yu et al. 2019) (e.g. SDG-6: Clean Water and Sanitation; SDG-14: Life Below Water; and SDG-15: Life on Land). River water quality evaluation uses a variety of water quality indices, including the National Sanitation Foundation (NSF) water quality index, the aquatic toxicity index

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(Wepener et al. 1999), the overall pollution index (Sargaonkar and Deshpande 2003), and the Oregon WQI (Cude 2001). The application of water quality indices in various contexts using contemporary approaches was examined by Abbasi and Abbasi (2012). Uddin et al. (2021) examined the components, applications, and uncertainties of different WQIs. By assigning weights to specific indicators depending on their permitted limitations, the weighted arithmetic Water Quality Index (WQI), devised by Horton (1965) is applicable at a local to regional scale (Tyagi et al. 2013), and is the reason that it has been applied in this study. The disadvantage of this index is that the chosen parameters and weights may have an impact on the results derived. Additionally, it only provides an indication of the general status of the water quality (Kumar and Dua, 2009), excluding specific parameter values. For the purpose of monitoring and evaluating water quality, therefore, the ascertained WQI should be used in combination with other derived indices, from other mediums.

The use of satellite images has become more and more prevalent for mapping surface water quality (Kuhn et al. 2019; Yunus et al. 2020; Patel et al. 2020). This avenue enables the assessment of certain water quality parameters like the turbidity and algal content of waterbodies on a regular basis and along their entire stretch (Vanhellemont and Ruddick 2018; Yepez et al. 2018; Zhou et al. 2020), which may not always be possible through field measurements, where samples are often taken from select locations. The surface water quality of rivers, lakes, and inland water bodies has thus been evaluated using a number of spectral indices, including the Normalized Difference Turbidity Index (NDTI) (Lacaux et al. 2007; Garg et al. 2020), the Water Turbidity Index (WTI) (Ouni et al. 2019), and the Normalized Difference Chlorophyll Index (NDCI) (Mishra and Mishra 2012). Among them, the NDTI parameter is very useful for estimating the ambient turbidity (Lacaux et al. 2007), which can be taken as an indicator of the excess runoff or soil loss from the adjacent riparian zone (Subramaniam and Saxena 2011), possibly due to land use changes. However, remote assessments of water quality entail that satellite derived parameters be tallied against field measured values, and obtaining their correlation would enable greater implementation of this technique while also extending the ambit of traditional water quality assessments.

The present study used the weighted arithmetic WQI, in-situ measurements and remotely-derived indices to assess the water quality of a small alluvial stream. It addresses a data gap in assessing the temporal distribution of water quality parameters across a smaller river course, in a data-scarce region like the Himalayan foothills of northern West Bengal. Such studies are pertinent as the availability of the local aquatic habitat potential zones is governed by the longitudinal variation of water physiochemical properties and geomorphic attributes.

2. Objectives

The objectives of the present study thus are:

i. To measure the surface water quality along the Sutunga's river, which is situated in an agricultural landscape, throughout the monsoon, post-monsoon, and pre-monsoon periods using a weighted arithmetic-based WQI;

ii. To investigate seasonal turbidity, TSS, nitrate (NO_3-N), and chloride (Cl^-) concentrations along the river's longitudinal direction; and

iii. To use the NDTI parameter to assess river turbidity following prolonged rainfall events and high flow, with field validation.

3. Dataset and methods

3.1. Study area

The Sutunga is a right bank tributary of the Jaldhaka River (Figure 1), with its source in the western Duars region along the Himalayan foothills of West Bengal. Thereafter it flows in a south-east direction over this lowland piedmont tract. During the summer monsoon, the river has high water level and discharge, but remains partly dry in the other months. Bank erosion and local sand mining are prevalent along its course. This river's catchment is characterized by paddy, tobacco and jute farms, and tea plantations. During the dry season, cultivation on the riverbed is prevalent.

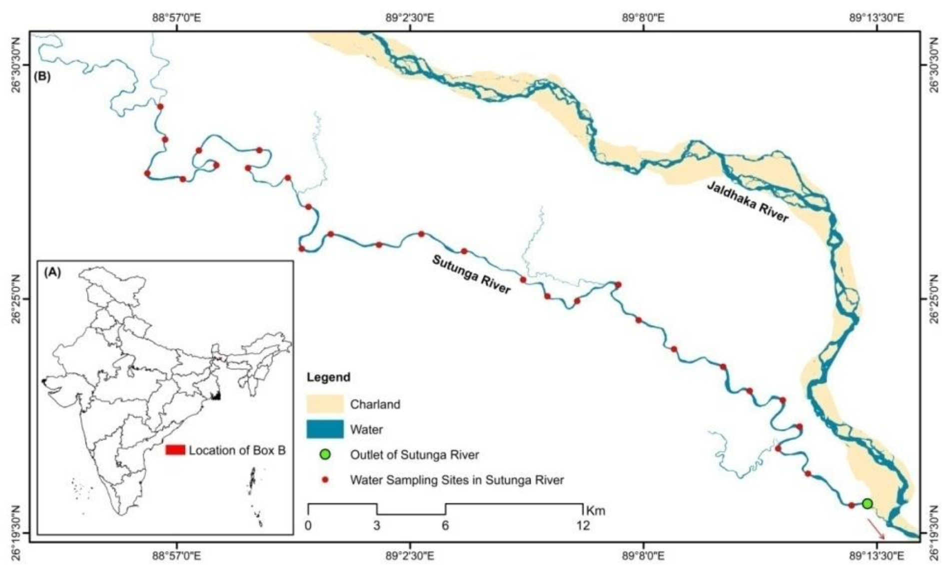

Figure 1: Study area location in northern West Bengal (A) and sample site locations (B) along the Sutunga River (a right bank tributary of the Jaldhaka).
Note: The sampling site closest to the Sutunga's outlet into the Jaldhaka River is r1, while the sampling site furthest from the outlet is r28.

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3.2. Sample collection and measurement

Moving upstream from the Sutunga River's outlet, 28 sites were chosen along the river from its demarcated reaches, each of ~2 km length (Figure 1). One water sample was taken from every site in each of the assessment periods. During the monsoon and post-monsoon periods of 2023 and pre-monsoon season of 2024, physicochemical parameters such as DO (dissolved oxygen), SPC (specific conductance), C (conductivity), TDS (total dissolved solid), pH, ORP (oxidation reduction potential), turbidity (FNU), TSS, NO_3-N (nitrate), and Cl^- (chloride) were measured at these sites using a YSI ProDSS Muti-parameter Digital Water Quality Meter (Table S1). In all, a total of 28 water samples were obtained at a depth of 20 cm below the water surface in each period, with 84 samples tested over the three periods. For monsoon 2023 and post-monsoon 2023, TSS (Total Suspended Solids) values were estimated using the equations proposed by Oliveira et al. (2018) based on measured turbidity values:

Wet season total suspended solids (TSS_{wet}): $TSS_{wet} = 0.86$ (turbidity) + 9.99 (Eq. 1)

Dry season total suspended solids (TSS_{dry}): $TSS_{dry} = 0.79$ (turbidity) + 4.36 (Eq. 2)

3.3. WQI determination

Horton (1965) proposed the Water Quality Index (WQI), which is based on a weighted arithmetic technique. It has been used here to categorize the surface water quality at specific locations along the Sutunga River's course, in accordance with the desirable limit of the Bureau of Indian Standards (BIS) and water quality classes (Chatterjee and Raziuddin 2002) (Table S2). The WQI values were calculated using seven parameters: DO (dissolved oxygen), C (conductivity), TDS (total dissolved solid), pH, Turbidity (FNU), NO_3-N (nitrate), and Cl^- (chloride), using the following formulae (Brown et al. 1970; Seth et al. 2014; Khan et al. 2023):

$$WQI = \frac{\sum(Q_i \times W_i)}{\sum W_i} \qquad \text{(Eq. 3)}$$

where, Q_i is the quality rating assigned to each parameter. It is determined as:

$$Q_i = 100 \times [(V_i - V_o)/(S_i - V_o) \qquad \text{(Eq. 4)}$$

where, V_i is the measured value of the ith parameter, V_o is its ideal value, and S_i is its acceptable value.

W_i is the unit weight of each parameter as determined by:

$$W_i = \frac{K}{S_i} \qquad \text{(Eq. 5)} \qquad \text{and}$$

$$\sum_{i=1}^{n} W_i = 1 \qquad \text{(Eq. 6)}$$

where, K is the constant, as determined by: $K = \frac{1}{\sum_{i=1}^{n}\frac{1}{S_i}}$ (Eq. 7)

Except for DO (14.6 mg/L), pH (7), and Turbidity (1), the ideal value for each parameter is '0'. The status of the surface water quality has been assessed in relation to the permitted limit for drinking water as per the Bureau of Indian Standards (CPCB, 2012) and the Central Pollution Control Board (CPCB, 2019) in Indian conditions. An example of the above computation is shown in Table S3.

3.4.Normalized Difference Turbidity Index (NDTI)

On the GEE platform, the Normalized Difference Water Index (NDWI) and Normalized Difference Turbidity Index (NDTI) were calculated using Sentinel-2A images for the years 2018, 2019, 2020, 2022, and 2023. These indices were extracted from cloud-free images, and the year 2021 was excluded due to the prevalent dense cloud cover. To avoid taking into account NDTI values from non-water pixels, we first determined the water surface presence along the Sutunga River. This is important as the water level in the river varies from the monsoon (often bankfull stage) to the non-monsoon period, when there are exposed bar deposits. We detected water occurrence within the channel the using Normalized Difference Water Index (NDWI) parameter as proposed by McFeeters (1996), which enhances water features as positive values (0 to +1) and suppresses soil and vegetation features as negative values (0 to -1). While the common drawback of this index is that built-up area noise is likely to be sensed as positive values (Xu 2006), its use was preferred here as there are almost no substantial built-up patches along the Sutunga's largely agricultural landscape dominated river corridor. The NDWI is expressed as follows:

$$NDWI = \frac{Green-NIR}{Green+NIR} \qquad \text{(Eq. 8)}$$

The Normalized Difference Turbidity Index (NDTI) was used to calculate the temporal turbidity concentration along the river course, where a greater value denotes a high concentration of turbidity and a lower value depicts clean water bodies, and its values range from +1 to -1 (Garg et al. 2020). It is expressed as follows:

$$NDTI = \frac{Red-Green}{Red+Green} \qquad \text{(Eq. 9)}$$

Sentinel-2A green (band 3) and red (band 4) bands were used to estimate the turbidity, and band 3 (green) and band 8 (NIR) were used to identify water pixels. These bands have a resolution of 10 m. The respective raster layers of the obtained NDTI values were clipped using the corresponding water surface shapefile for that time period as obtained from the pixels of the NDWI raster. The segment-wise mean NDTI values for the 28 reaches were computed using zonal statistics in ArcGIS 10.3.1. The mean NDTI values derived for each reach during August to September 2023 from the Sentinel 2A images were further used for comparison with the measured turbidity values of this monsoon period, with field water samples collected and measured using the YSI ProDSS instrument on September 17, 2023, from all 28 sites.

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3.5 Statistical analysis

Descriptive statistics were used to determine the mean ± SD, lowest and maximum concentration values of the water quality parameters. A one-way analysis of variance (ANOVA) was used to evaluate the seasonal differences in each water quality parameter between and among seasons, as well as to test the equality of means, as ANOVA indicates whether or not the tested means belong to being equal. A curve-fitting exercise done to examine the longitudinal concentration pattern of water quality parameters in terms of seasonality. In addition, correlation analysis determined the relationships between these parameters across seasons. The statistical analyses were performed using MS Excel 2007 and using R studio (R Foundation Team 2024).

3.6 Spatial mapping analysis

We grouped and mapped sites into five categories based on WQI values: excellent water quality (0 to 25), good water quality (more than 25 to 50), poor water quality (more than 51 to 75), extremely bad water quality (more than 75 to 100), and unsuitable water quality (more than 100), based on the method formulated by Chatterjee and Raziuddin (2002). Segment-wise turbidity along the river was mapped using the respective mean NDTI values.

4. Results and discussion

4.1. Seasonality of physicochemical parameters and WQI

Table 1 presents descriptive statistics for seasonal sampled water quality parameters for each of the 28 sites, and the seasonal significant level was determined using one-way ANOVA (Table 2). Box and whisker plots (Figure 2) show the seasonal distribution of water quality parameters (DO, C, SPC, ORP, pH, FNU, TSS, TDS, NO3-N, CL, and WQI). The present investigation found that post-monsoon dissolved oxygen (DO) levels were higher (9.77 ± 0.63 mg/L) than monsoon levels (8.77 ± 0.24 mg/L), while pre-monsoon DO levels decreased to 9.32 ± 0.92 mg/L. This decrease is due to increased turbidity and total suspended solids (TSS) in river water during the flood event and monsoon, which reduces DO level (Van Vliet et al., 2023). The increase in DO following the monsoon has been attributed to the entry of DO-rich freshwater (Shetty et al., 2013). The oxidation-reduction potential (ORP) fluctuated significantly, decreasing from +41.02 ± 4.61 mV during the monsoon to -1.45 ± 13.81 mV after the monsoon, then ascending to +39.13 ± 24.65 mV before the monsoon. There were statistically significant changes between the monsoon and post-monsoon periods ($p < 0.001$), as well as the post-monsoon and pre-monsoon periods ($p < 0.001$), but no significant difference was found between the monsoon (2023) and pre-monsoon (2024). A higher positive value of the ORP indicates that the water has more oxygen and provides a better habitat condition (Nyieku et al., 2021).

Table 1: Descriptive statistics of water quality parameters for the Sutunga River during the different examined periods

Parameters with units	Monsoon 2023				Post-Monsoon 2023				Pre-Monsoon 2024			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
DO (mg/L)	8.77	0.24	8.42	9.35	9.77	0.63	7.97	10.99	9.32	0.92	7.24	11.44
SPC (µS/cm)	109.43	3.61	103.60	117.50	109.03	7.99	95.70	133.40	107.99	14.23	86.20	162.00
C (µS/cm)	119.78	3.98	112.80	128.60	108.77	9.13	91.90	135.10	112.98	16.05	96.40	182.10
TDS (mg/L)	71.14	2.39	67.00	76.00	70.82	5.28	62.00	87.00	70.14	9.26	56.00	105.00
pH	7.13	0.13	6.93	7.45	7.07	0.16	6.67	7.29	7.22	0.41	6.65	8.68
ORP (mV)	41.02	4.61	31.40	48.50	-1.45	13.81	-45.10	13.60	39.13	24.65	-12.80	61.70
NO_3-N (mg/L)	0.94	0.31	0.47	1.72	1.27	0.28	0.70	1.93	14.81	8.88	2.02	35.98
Cl^- (mg/L)	5.66	1.13	3.74	9.07	7.71	1.67	4.55	12.29	9.40	9.94	3.59	44.95
Turbidity (FNU)	4.35	2.56	2.04	14.73	3.05	1.19	1.54	6.52	2.09	0.94	0.62	4.67
TSS (mg/L)	13.73	2.20	11.74	22.66	6.77	0.94	5.58	9.51	3.71	1.01	2.15	6.50

Note: N = 28 in each of the three periods; total 84 samples.

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Table 2: Results of ANOVA: Single Factor (statistical significance set at $\alpha = 0.05$)

Water quality parameters	Between Monsoon 2023 and Post-monsoon 2023		Between Post-monsoon 2023 and Pre-monsoon 2024		Between Monsoon 2023 and Pre-monsoon 2024		Among all seasons	
	F	p-value	F	p-value	F	p-value	F	p-value
DO (mg/L)	61.364	< 0.001	4.559	0.037	9.484	0.003	16.272	< 0.001
SPC (µS/cm)	0.058	0.811	0.114	0.737	0.270	0.606	0.167	0.847
C (µS/cm)	34.217	< 0.001	1.456	0.233	4.732	0.034	7.265	0.001
TDS (mg/L)	0.082	0.775	0.113	0.738	0.302	0.585	0.181	0.835
pH	2.556	0.116	3.500	0.067	1.317	0.256	2.440	0.094
ORP (mV)	238.362	< 0.001	57.758	< 0.001	0.160	0.691	59.012	< 0.001
NO_3-N (mg/L)	18.045	< 0.001	65.034	< 0.001	68.272	< 0.001	66.600	< 0.001
Cl^- (mg/L)	28.949	< 0.001	0.781	0.381	3.896	0.054	2.852	0.064
Turbidity (FNU)	5.966	0.018	11.213	0.001	19.270	< 0.001	12.241	< 0.001
TSS (mg/L)	237.689	< 0.001	137.211	< 0.001	479.666	< 0.001	328.684	< 0.001
WQI	11.202	0.001	1.808	0.184	18.018	< 0.001	12.745	< 0.001

Note: DO- Dissolved Oxygen, SPC – Specific Conductance, C- Conductivity, TDS- Total Dissolved Solids, ORP – Oxidation-Reduction Potential, TSS- Total Suspended Solids, WQI- Water Quality Index

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Such alterations occur as a result of the fluctuating water level in the river, with higher discharge during the monsoon bringing in more sediment and thereby increasing the overall turbidity (Kumar et al., 2019; Sahu et al., 2019; Siddha and Sahu, 2022), while a decline in the water level in the post-monsoon period would cause less dilution of the nitrate and chloride concentrations and thus report higher values (Oberleitner et al., 2020; Chakraborty, 2021). Agricultural runoff too plays a role in conditioning the river water quality as the cropping pattern varies across seasons (Willis and McDowell, 1982; Casali et al., 2008; Giri, 2021). Overall, in the post-monsoon period and pre-monsoon period, we observe greater stressors on the stream habitat environment, in terms of reduced ORP and increased concentrations of both NO_3-N and Cl^-, while this is offset to some degree by the reduced turbidity and consequently TSS. It also indicates that the water quality of alluvial rivers and associated ecosystems is influenced by seasonal flow pulse characteristics (Nilsson and Renofalt, 2008; Sabater and Tockner, 2009; Puig et al., 2016), since monsoon rainfall events dominate in the studied river's inundation hydrology.

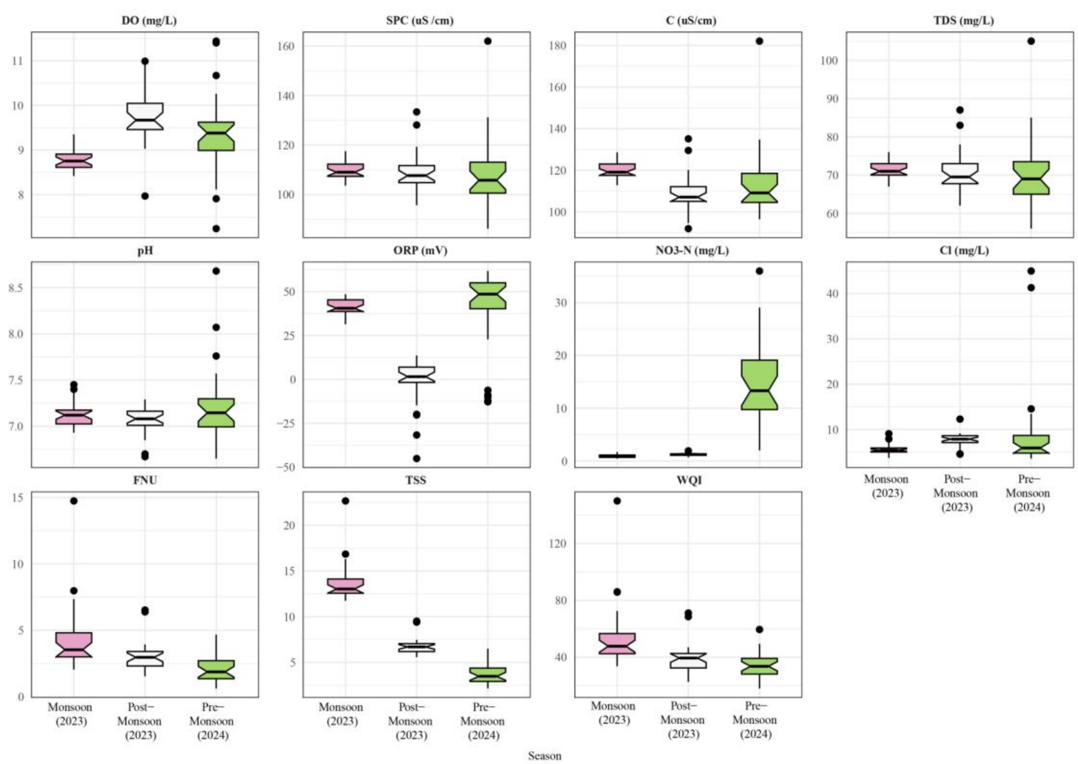

Figure 2: Box-plot showing seasonal and site-wise variability in measured water quality parameters and WQI

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Several physio-chemical parameters (DO, conductivity, TDS, pH, NO_3-N, turbidity) were measured for assessing surface water quality at 28 sites along the Sutunga River during the monsoon (2023), post-monsoon (2023), and pre-monsoon (2024) periods. Overall WQI of the Sutunga River was 54.80 during the monsoon, 38.36 after the monsoon, and 33.89 before the monsoon (Figure 3, Table 3). Significant variation was found in WQI between the monsoon and post-monsoon seasons ($p = 0.001$), but no significant difference was found between the post-monsoon and pre-monsoon periods ($p = 0.184$). WQI values varied by site, with the greatest values observed at r9 during the monsoon (149.90), r28 during post-monsoon (71.07), and r11 during pre-monsoon (59.46). The lowest WQI values were observed at r15 during the monsoon (33.67), r21 post-monsoon (22.63), and r17 pre-monsoon (17.99). Water quality parameters vary along the river course, influenced by bank and substrate composition, presence and absence of vegetation along the banklines, flow velocity, and agricultural runoff (Nilsson and Renofalt, 2008; Giri, 2021; Siddha and Sahu, 2022). This variability emphasizes the importance of conducting site-specific investigations to better understand the underlying reasons of seasonal fluctuations.

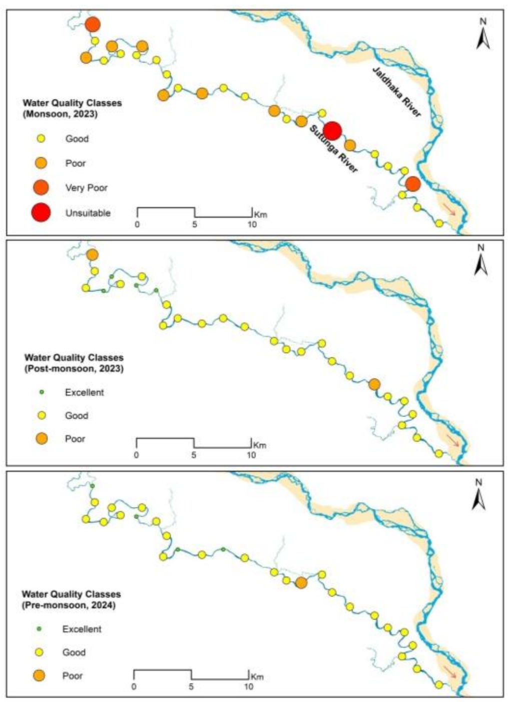

Figure 3: Variations in the Sutunga River's surface water quality (based on WQI) along the longitudinal direction during the monsoon and post-monsoon seasons in 2023, as well as the pre-monsoon season in 2024

Table 3: Computed Water Quality Index (WQI) values and Rating Status at 28 sites along the Sutunga River

Site ID	Monsoon 2023			Post-monsoon 2023			Pre-Monsoon 2024		
	Computed WQI	Water quality Classes	Grade	Computed WQI	Water quality Classes	Grade	Computed WQI	Water quality Classes	Grade
r1	48.01	Good	B	35.24	Good	B	31.49	Good	B
r2	45.88	Good	B	31.73	Good	B	30.00	Good	B
r3	35.19	Good	B	45.02	Good	B	48.25	Good	B
r4	85.73	Very Poor	D	28.07	Good	B	26.88	Good	B
r5	47.37	Good	B	40.25	Good	B	33.27	Good	B
r6	45.72	Good	B	40.51	Good	B	33.47	Good	B
r7	41.95	Good	B	68.48	Poor	C	49.43	Good	B
r8	52.06	Poor	C	39.19	Good	B	41.17	Good	B
r9	149.90	Unsuitable	E	42.51	Good	B	33.70	Good	B
r10	49.43	Good	B	42.68	Good	B	36.57	Good	B
r11	50.94	Poor	C	35.00	Good	B	59.46	Poor	C
r12	43.93	Good	B	39.77	Good	B	43.99	Good	B
r13	70.95	Poor	C	32.62	Good	B	33.45	Good	B
r14	36.29	Good	B	46.96	Good	B	33.85	Good	B
r15	33.67	Good	B	37.73	Good	B	22.35	Excellent	A
r16	72.48	Poor	C	39.71	Good	B	39.63	Good	B
r17	37.76	Good	B	37.28	Good	B	17.99	Excellent	A
r18	50.21	Poor	C	39.54	Good	B	36.70	Good	B
r19	42.56	Good	B	43.81	Good	B	38.51	Good	B
r20	43.67	Good	B	23.99	Excellent	B	27.14	Good	B
r21	39.90	Good	B	22.63	Excellent	A	24.31	Excellent	A
r22	70.17	Poor	C	32.90	Good	B	27.55	Good	B

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r23	53.76	Poor	C	24.69	Excellent	B	36.36	Good	B
r24	40.61	Good	B	42.85	Good	B	41.71	Good	B
r25	46.35	Good	B	22.70	Excellent	A	28.32	Good	B
r26	65.10	Poor	C	27.33	Good	B	38.95	Good	B
r27	48.68	Good	B	39.95	Good	B	32.53	Good	B
r28	85.99	Very Poor	D	71.07	Poor	C	24.76	Excellent	A
Overall	**54.80**	**Poor**	**C**	**38.36**	**Good**	**B**	**33.89**	**Good**	**B**

Note: The sampling site closest to the Sutunga's outlet into the Jaldhaka River is r1, while the sampling site furthest from the outlet is r28.

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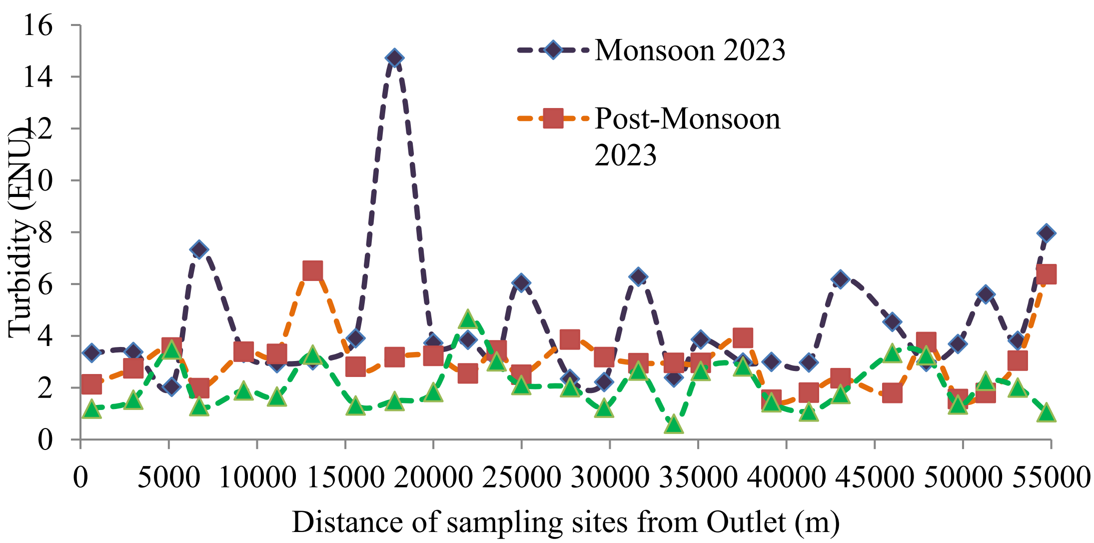
4.2. Seasonal patterns in nitrate-N, chloride, turbidity and TSS along the river course

Among water quality parameters, nitrate and chloride are often considered as indicators of agricultural runoff influence in surface waters (Granato et al., 2015; Wang and Li, 2019). The concentration of NO_3-N varies along the Sutunga River at various sites in different seasons. The river flows through an agricultural area, and nitrate is one of the contaminants derived from fertilizers. During the monsoon, greater runoff from the adjacent agricultural plots can transfer more nitrates into the river, as a result of the enhanced landscape connectivity. Furthermore, agricultural expansion, excessive nitrogen-based fertilizer use in river catchments, and vegetation buffers along river corridors all have a role in nitrate concentration changes (Lintern et al., 2018). Ascertaining this river's nitrate pollution status and seasonal variations is critical for its floodplain ecosystem management. Longitudinal variation in nitrate concentrations depends on several factors, including excessive amounts of runoff with low nitrate concentrations during the wet season, runoff from agricultural land after rainstorms, and rivers being recharged by nitrate-concentrated groundwater during the dry season (Billy et al., 2013).



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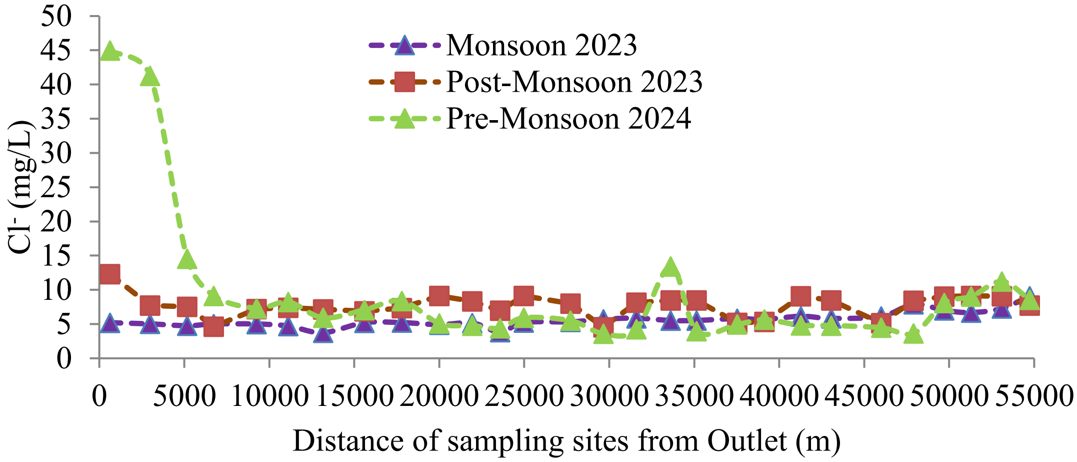

Figure 4: Seasonal variation in nitrate and chloride concentration at different sampling sites from the outlet, along various reaches of Sutunga River.

Nitrate concentrations were higher in the upper-reach sampling locations during the monsoon than in lower-reach sampling sites (Figure 4). This could arise from a possible dilution of the nitrate concentration as the volume of flow in the river increases downstream (Meixner et al., 2007). Contrastingly, nitrate levels were greater near the outlet and upper-middle sample sites during the post-monsoon season. Nitrate concentrations in water samples ranged from 0.47 to 1.72 mg/L during the monsoon, from 0.70 to 1.93 mg/L after the monsoon and from 2.02 to 35.98 mg/L before the monsoon. The average NO_3-N concentration in water samples collected during and after the monsoon and pre-monsoon were 0.94 mg/L,1.27 mg/L and 14.81 mg/L, respectively. According to BIS guidelines, the nitrate concentration in this river course is much below the acceptable level (nitrate: 45 mg/L).

Chloride concentration in water samples ranged from 3.74 to 9.07 mg/L during the monsoon, from 4.55 to 12.29 mg/L after the monsoon and from 3.59 to 44.95 mg/L during the pre-monsoon (Figure 4). According to BIS guidelines, none of the sampled sites had a value greater than the desired limit (250 mg/L). Similar to the pattern displayed by nitrate concentration, post-monsoon chloride concentrations were slightly higher than that during the monsoon. Longitudinal variations are apparent, with sites further away from the Sutunga's outlet into the Jaldhaka having overall greater chloride concentration. The increase in downstream flow may possibly dilute this parameter.

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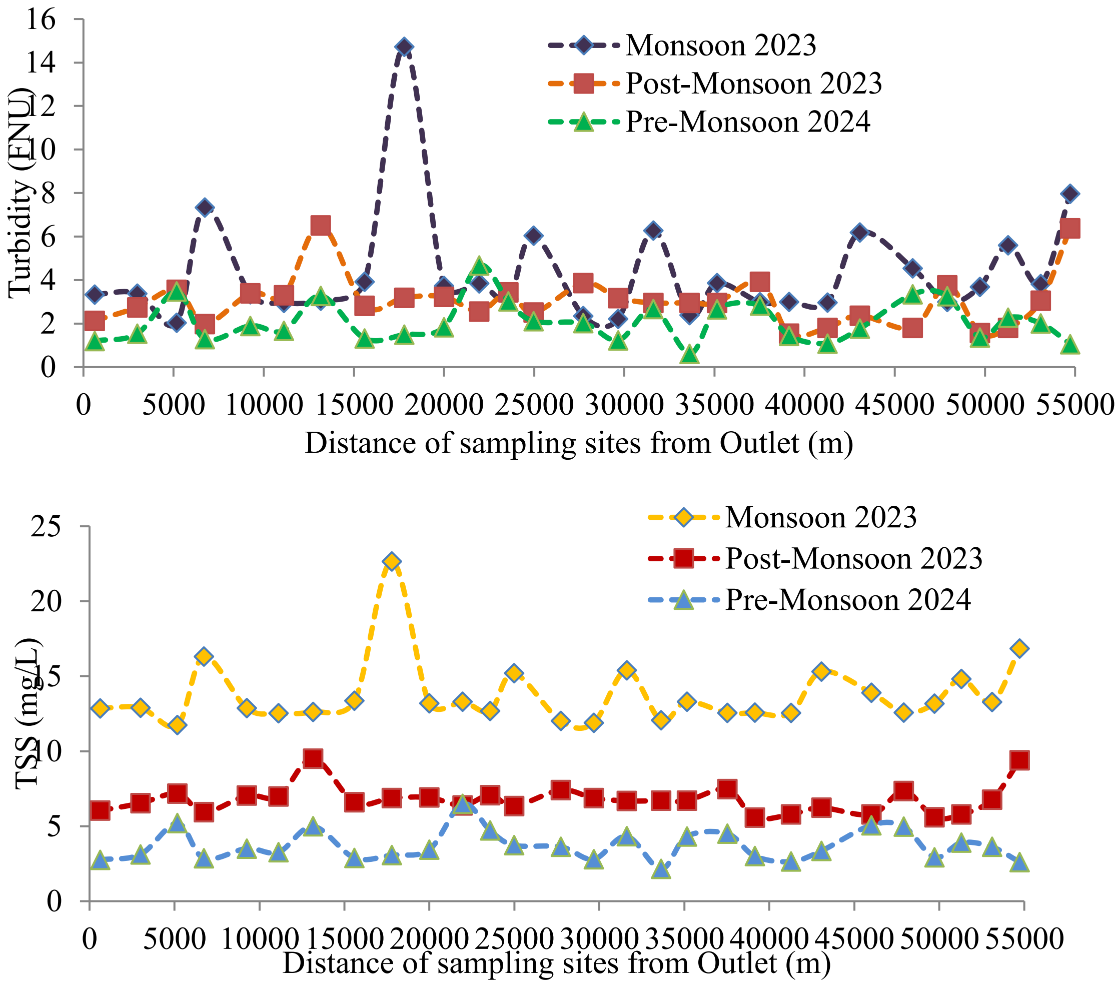

Figure 5: Seasonal variation in turbidity and TSS concentration at different sampling sites from the outlet, along various reaches of Sutunga River.

Expectedly, turbidity values were higher during the monsoon period due to the greater runoff from fields that transfers soil and sediment into the river (Figure 5). The total suspended solids (TSS) concentration in water samples was consequently also greater during the monsoon (mean ± SD = 13.73 ± 2.20 mg/L) than in the post-monsoon (mean ± SD = 6.77 ± 0.94 mg/L) and pre-monsoon (mean ± SD = 3.71 ± 1.01). However, these are not measured values, but rather estimates based on the earlier stated equations and derived from the measured turbidity values. According to BIS guidelines, estimated TSS values for both seasons were lower than the desired limit (TSS = 500 mg/L). During the dry season and pre-monsoon season, in-channel cultivation is quite common and this increases upstream from the river's mouth. Related to this, nitrate concentration is more in upper reach sites compared to downstream sites.

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Table 4: Curve fitting on the concentration of water quality parameters along longitudinal direction

Water quality parameters	**Seasons**	**R^2 for best-fit line**								
		Exponential	Linear	Logarithmic	Polynomial (order-2)	Polynomial (order-3)	Polynomial (order-4)	Polynomial (order-5)	Polynomial (order-6)	Power
Cl^- (mg/L)	Monsoon 2023	.613	.616	.276	.794	.796	.815	.821	.822	.274
	Post-monsoon 2023	.001	.000	.050	.084	.095	.225	.424	.430	.024
	Pre-monsoon 2024	.206	.226	.627	.600	.749	.871	.889	.890	.541
C (µS/cm)	Monsoon 2023	.227	.227	.270	.343	.393	.394	.394	.592	.268
	Post-monsoon 2023	.237	.244	.510	.607	.610	.697	.717	.776	.477
	Pre-monsoon 2024	.120	.081	.115	.084	.176	.177	.186	.186	.165
DO (mg/L)	Monsoon 2023	.030	.032	.182	.171	.407	.418	.430	.461	.176
	Post-monsoon 2023	.013	.010	.124	.151	.153	.482	.525	.536	.144
	Pre-monsoon 2024	.232	.229	.027	.335	.537	.573	.576	.613	.027
Turbidity (FNU)	Monsoon 2023	.017	.002	.006	.004	.112	.114	.119	.153	.016
	Post-monsoon 2023	.021	.003	.000	.005	.253	.292	.388	.451	.000
	Pre-monsoon 2024	.000	.000	.010	.030	.036	.062	.102	.154	.009
NO_3-N (mg/L)	Monsoon 2023	.818	.776	.607	.779	.780	.781	.782	.807	.717
	Post-monsoon 2023	.088	.102	.041	.198	.648	.648	.744	.767	.042
	Pre-monsoon 2024	.680	.780	.540	.786	.789	.853	.868	.868	.411
ORP (mV)	Monsoon 2023	.352	.349	.268	.364	.399	.411	.458	.488	.280
	Post-monsoon 2023		.112	.309	.298	.521	.535	.574	.575	

	Pre-monsoon 2024		.262	.167	.356	.560	.590	.591	.599	
pH	Monsoon 2023	.587	.585	.619	.612	.649	.653	.667	.668	.615
	Post-monsoon 2023	.008	.009	.007	.076	.165	.194	.197	.218	.008
	Pre-monsoon 2024	.276	.259	.086	.282	.602	.603	.637	.723	.095
SPC (µS/cm)	Monsoon 2023	.238	.239	.291	.376	.426	.426	.426	.616	.290
	Post-monsoon 2023	.268	.270	.571	.666	.666	.750	.760	.832	.548
	Pre-monsoon 2024	.288	.226	.244	.226	.355	.355	.362	.363	.295
TDS (mg/L)	Monsoon 2023	.251	.252	.321	.399	.430	.430	.430	.638	.317
	Post-monsoon 2023	.264	.267	.567	.661	.661	.745	.754	.835	.544
	Pre-monsoon 2024	.285	.225	.240	.225	.357	.358	.366	.368	.290
TSS (mg/L)	Monsoon 2023	.006	.002	.006	.004	.112	.114	.119	.153	.010
	Post-monsoon 2023	.008	.003	.000	.005	.253	.292	.388	.451	.000
	Pre-monsoon 2024	.000	.000	.010	.031	.037	.063	.102	.154	.011
WQI	Monsoon 2023	.001	.000	.001	.001	.110	.113	.116	.151	.003
	Post-monsoon 2023	.031	.009	.000	.012	.282	.361	.435	.520	.006
	Pre-monsoon 2024	.055	.056	.010	.073	.149	.163	.267	.278	.013

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To further assess the longitudinal variation in water quality parameters, a curve-fitting exercise was conducted. The seasonal concentration of water quality parameters does not exhibit any distinct trend (Table 4). The polynomial (order 6) best-fit line captures the high and low concentrations of water quality along the Sutunga in a nonlinear behaviour. Water depth and flow pattern are critical elements along a river's longitudinal profile that influence water quality parameters (Nilsson and Renofalt, 2008; Harvey et al., 2019). Tributary inputs, higher flows, low flow zones (bend apex) due to meander formation (Trush et al., 2000), flow discontinuity by bridge or sand mining tracks, riparian vegetation and in-stream agricultural patches along the river course (Behbahani et al. 2017; Anderson et al. 2019; Mondal and Patel 2021) are other potential reasons of irregular water quality variations.

3.3 Correlation among physio-chemical parameters

The correlation coefficient between pH and DO is greater than 0.5 (Figure 6), indicating that pH fluctuations influence the amount of dissolved oxygen. Higher pH levels increase the soluble capacity of oxygen in river water, resulting in higher DO levels, while lower pH values, indicating more acidic conditions, may reduce the soluble capacity of oxygen, resulting in lower DO levels. Conductivity, TDS, and SPC are positively correlated ($r > 0.9$). The significant relationship between turbidity, TSS and WQI indicates that these markedly influence the overall water quality (Anthony et al., 2007), and thus assessing their seasonal trends is critical for evaluating water resources and aquatic ecosystems. High levels of turbidity and TSS can impair aquatic ecosystems by decreasing light penetration, interfering with photosynthesis, and disturbing habitat for aquatic species (Vohs et al., 1993; Bilotta and Brazier, 2008).

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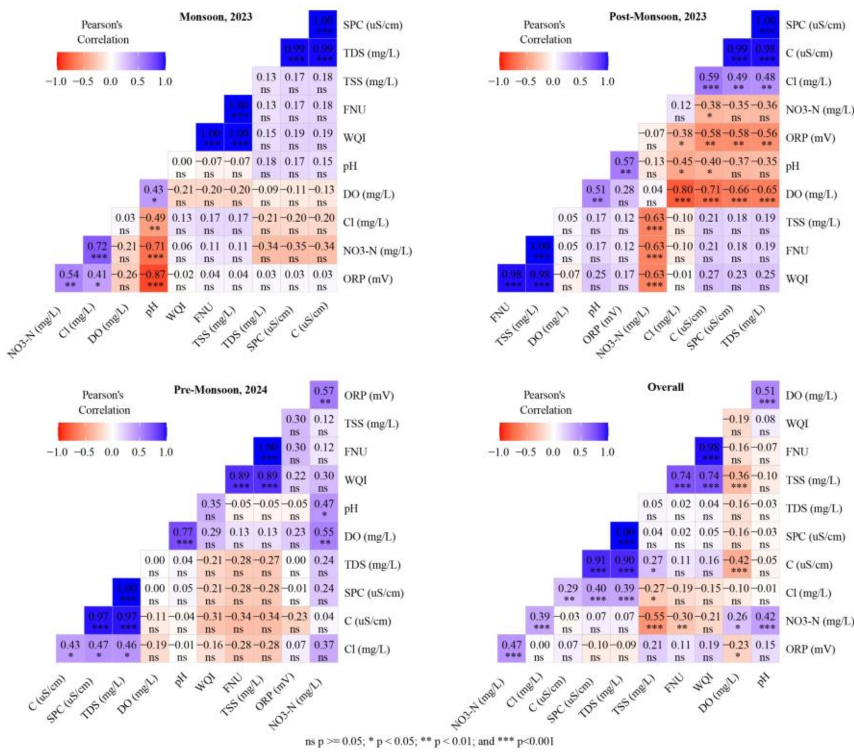

Figure 6: Correlation matrix of the measured water quality parameters

3.4 Spatial-temporal variation in NDTI and comparison with measured turbidity

The monsoon season turbidity concentration along several reach segments of the Sutunga River for the years 2018, 2019, 2020, 2022, and 2023 were analysed from the derived NDTI values. We employed zonal statistics to extract the mean NDTI values and mapped them for reach-wise analysis (Figure 7). The generally negative values denote largely relatively clear water (Lacaux et al. 2007). Compared to values in the lower reach segments (R4 to R14), turbidity concentrations are higher in upper reach segments (R15 to R28). Measured turbidity (FNU) in water samples varied from 2.04 to 14.73 during the monsoon, from 1.54 to 6.52 during the post-monsoon and from 0.62 to 4.67 during pre-monsoon. Acceptable and permitted limits are 1 and 5, respectively, based on BIS standards.

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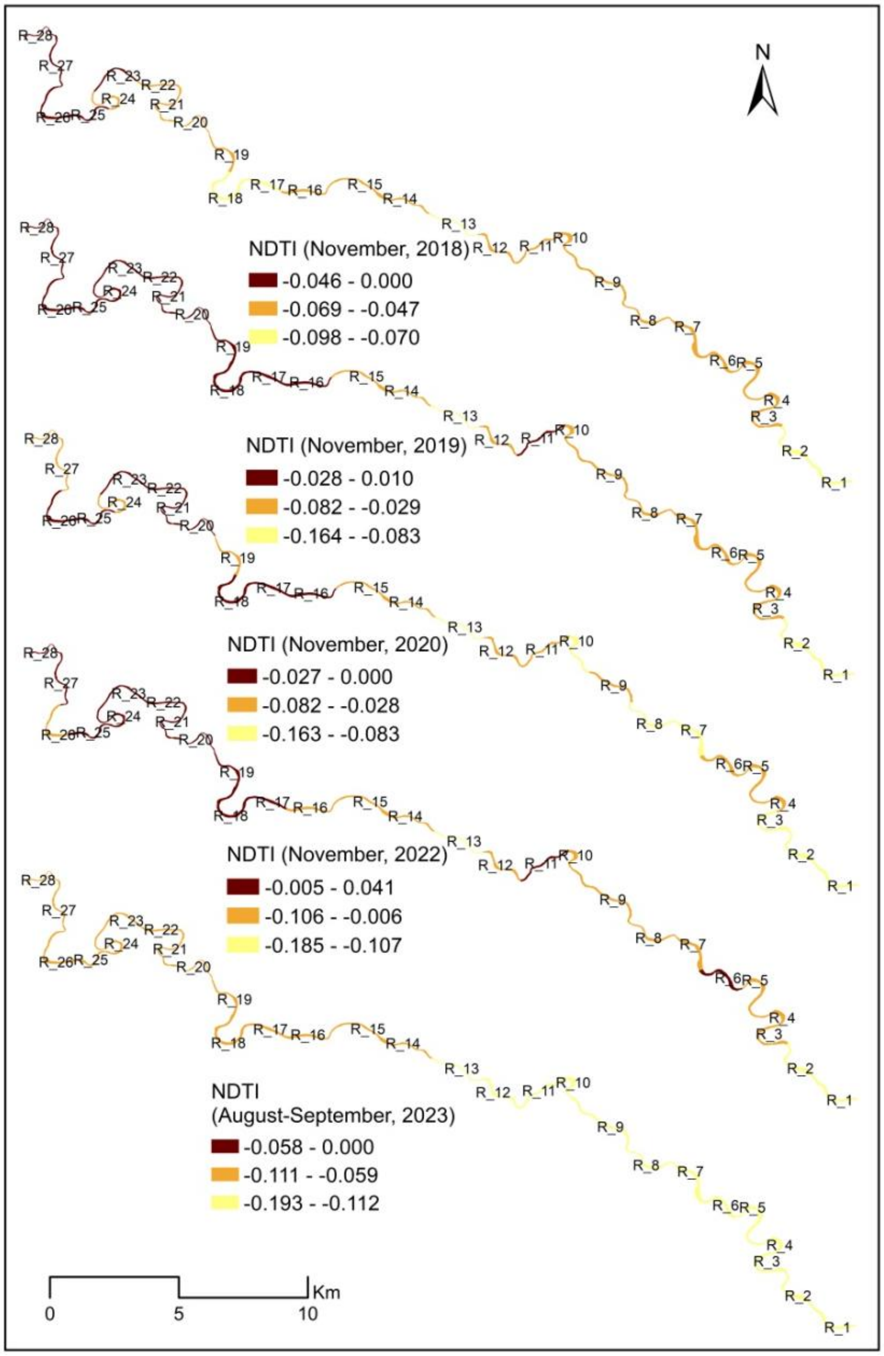

Figure 7: Spatio-temporal pattern of NDTI values along various reaches of the Sutunga River.

Note: The sampling site closest to the outlet is r1 (Reach 1), while the sampling site furthest from the outlet is r28 (Reach 28). Natural break classification (Jenks) was used to classify the NDTI values.

Reach R1, which is close to the Sutunga and Jaldhaka River confluence zone, is where marked temporal variability is observed in the NDTI values (Figure 8). This may occur due to the episodic floods in the Jaldhaka, with a higher water level therein than in the Sutunga, resulting in backflow into the tributary channel or a blockage of its outflow. Images from the monsoon and post-monsoon periods of 2022 report overall higher values than those of other time periods. During August 2022, the Jaldhaka had continuously flowed at higher than the indicative danger level for the river due to the heavy rainfall in the region (I&WD, 2023) and this high discharge throughout the monsoon period and into the post-monsoon season may have induced the greater NDTI values recorded.

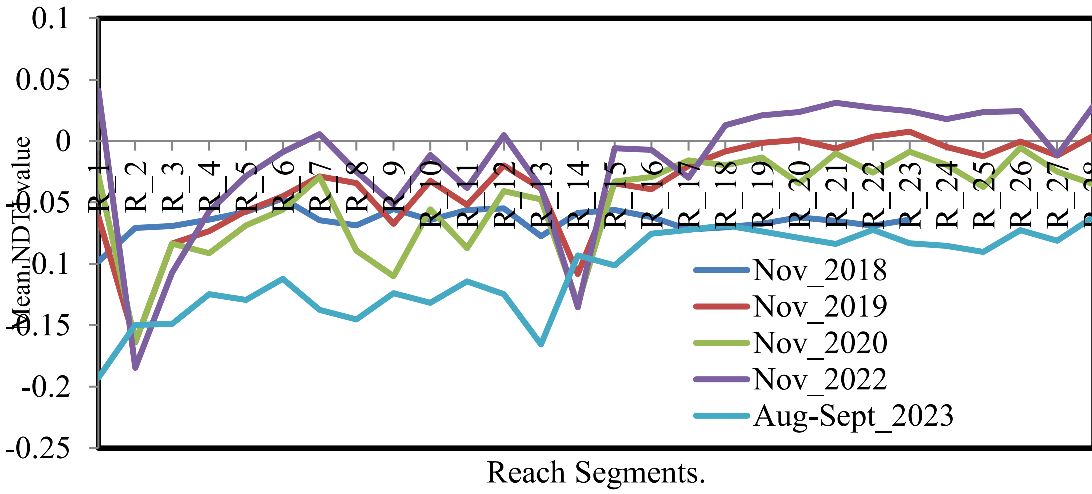

Figure 8: Temporal pattern of mean NDTI values for each reach.

Note: The sampling site closest to the outlet is R1 (Reach 1), while the sampling site furthest from the outlet is R28 (Reach 28).

Comparisons of the observed/measured turbidity (FNU) values of the 28 reaches with the mean NDTI values extracted from the Sentinel images for August to September 2023, revealed a positive correlation (R^2 = 0.71), as indicated by the logarithmic best fit line (Figure 9). Deriving such a relation is useful since this allows the estimation of the probable river turbidity in a reach if direct measurements cannot be taken. Furthermore, this enables repeat estimations to be elicited from multiple historical as well as new images. Especially during the rainy season, when in-situ measurements are difficult and time-consuming, spectral indices such as the NDTI can be useful for monitoring and assessing water quality.

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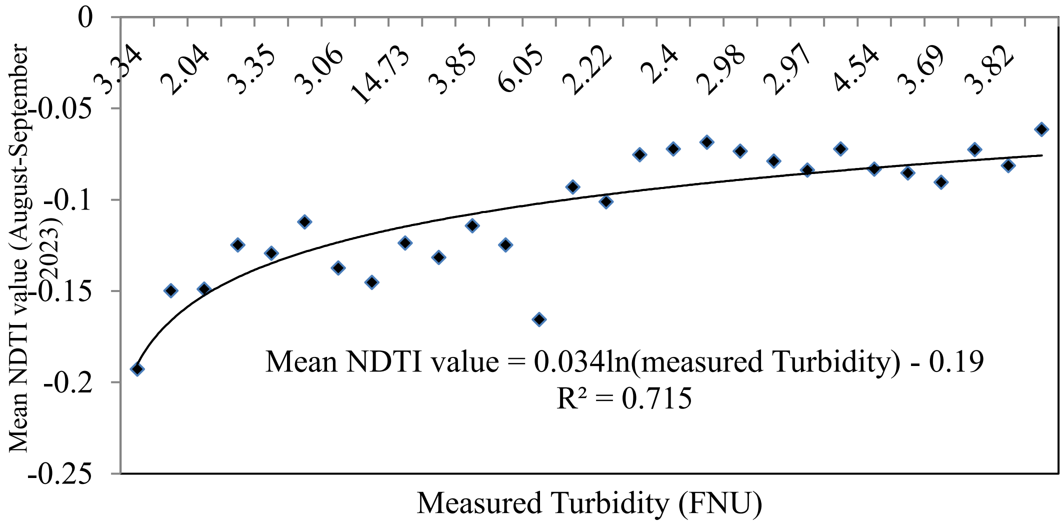

Figure 9: Best-fit line between the reach-wise mean NDTI values (August-September, 2023) and the field-measured turbidity (FNU).

5. Conclusion

The importance of water quality monitoring in small streams, particularly those coursing through intensively cultivated landscapes, is paramount, as they can demonstrate marked fluctuations in their physicochemical parameters on a seasonal basis. Such effects are more dampened down in the case of larger rivers due to dilution of the chemical signals within the higher discharge. Smaller streams thus provide a sensitive medium to assess land transformations in a region. Here, we have examined the relevant water quality parameters for a small river, the Sutunga, that flows across the Himalayan foothill zone in eastern India. Seasonal changes in its water quality parameters are evident, with the diminishing flow in the post-monsoon and pre-monsoon indicative of greater stress on the local stream habitat conditions.

WQI is an important component in determining a river's overall surface water quality. The current study demonstrates that water quality status deteriorates during the monsoon months due to higher turbidity and TSS concentration, and improves afterward. High flows and prolonged rainfall events have a significant impact on the alluvial river's water quality status. One-way ANOVA results demonstrate significant differences in DO, NO_3-N, turbidity and TSS. Such variability highlights the significance of carrying out site-specific investigations across the river to better understand the underlying causes of seasonal changes.

Even then, being part of a large agricultural landscape bereft of substantial built-up tracts, the river reports good WQI ratings in most of its examined 28 sites in the assessed seasons. Fluctuations in the turbidity levels are also symptomatic of possible variations in the water level of the tributary and main stream, but the paucity of available data in this respect precludes any further surmises. The ascertained relation between the field measured turbidity and satellite image derived NDTI values can be used to monitor this river remotely and repetitively. Such relations, if derived and confirmed for other rivers, can further advance river water quality assessments over wider areas and elicit data at more frequent intervals.

This study concentrates on examining overall surface water quality, the longitudinal distribution pattern of water quality parameters, and the field validation of NDTI in a small alluvial river. From a geomorphologic standpoint, alluvial rivers experience morphological change and bankline shifting during the monsoon season, which occurs site-specifically. Further research can include evaluations of water quality for particular reaches experiencing such morphological changes to discern any causal links between channel alteration and water quality. Inclusion of flow depth and velocity information and relating these to water quality evaluations along the river's course is a further avenue of research.

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Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis was performed by DB. The first draft of the manuscript was written by both DB and PPP. All authors have read and approved the final manuscript.

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