ASSESSING RURAL WATER QUALITY THROUGH INDEX MODELS: EVALUATIONS FROM THE VILLAGES OF INDORE

M. Tech. Thesis

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ASSESSING RURAL WATER QUALITY THROUGH INDEX MODELS: EVALUATIONS FROM THE VILLAGES OF INDORE

A THESIS

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **ASSESSING RURAL WATER QUALITY THROUGH INDEX MODELS: EVALUATIONS FROM THE VILLAGES OF INDORE** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DEPARTMENT OF CIVIL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July 2023 of joining the M.Tech. program to May 2025 under the supervision of Dr. Mayur Shirish Jain, Assistant Professor, Department of Civil Engineering, Indian Institute of Technology Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Deborshee Sinha

Signature of the student
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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

Signature of the Supervisor of M.Tech. thesis (with date)
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Deborshee Sinha has successfully given his/her M.Tech. Oral Examination held on **24th May, 2025**.

Signature(s) of Supervisor(s) of M.Tech. thesis
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Deborshee Sinha (2302104011)

Date: 23/05/2025

CERTIFICATE

This is to certify that the Project Work entitled "ASSESSING RURAL WATER QUALITY THROUGH INDEX MODELS: EVALUATIONS FROM THE VILLAGES OF INDORE" is bonafide work of Mr. Deborshee Sinha in partial fulfilment of the academic requirements for the award of Post Graduate Programme in Water, Climate and Sustainability (WCS). This work is carried out by him, under my guidance and supervision.

Signature of Guide

Dr. Mayur Shirish Jain

DEDICATION

This thesis is dedicated to **my beloved parents**, whose unwavering love, enduring sacrifices, and constant encouragement have been the guiding force behind every step of my academic journey.

ABSTRACT

Safe drinking water access continues to be a key issue in rural India, with chemical and microbial contaminants being the main cause. This research evaluates the quality of water from five villages in Indore: Borkhedi, Gokanya, Harsola, Memdi, and Simrol, through detailed physicochemical and heavy metal analysis of 36 water samples. 24 parameters were examined, viz., fluoride, nitrate, COD, BOD, TSS, and heavy metals such as Mn, Zn, Fe, Ni, Pb, and Cr. On the basis of models like Dojlido, Bascaron, Brown, SRDD, Aquatic Toxicity Index, West Java, Dinius, and Entropy-weighted WQI, the research compared the efficiency of various Water Quality Index (WQI) models. Results indicated extensive pollution with fluoride content above 2.4 mg/L, and organic contamination was widespread at most sites. Whereas the Dojlido model presented inflated WQI values, the Entropy-weighted, Brown, and Bascaron indices indicated contamination more accurately. Sensitivity analysis also identified Pb, Cr, and Cd as the most significant parameters impacting WQI values. The research concludes that Bascaron, Brown, and Entropy-weighted models present a balanced and context-suitable platform for rural water quality monitoring and suggests their implementation for region-specific sustainable water management.

Keywords: Rural Water Quality, AHP, Water Quality Index (WQI), Physicochemical Parameters, Heavy Metal Analysis, Entropy Weighting Method, Sensitivity Analysis.

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ACRONYMS

Abbreviation	Full Form
WQI	Water Quality Index
EWQI	Entropy-Weighted Water Quality Index
APHA	American Public Health Association
BOD	Biochemical Oxygen Demand
COD	Chemical Oxygen Demand
DO	Dissolved Oxygen
TSS	Total Suspended Solids
VSS	Volatile Suspended Solids
EC	Electrical Conductivity
pH	Potential of Hydrogen
NTU	Nephelometric Turbidity Units
WHO	World Health Organisation
CPCB	Central Pollution Control Board (India)
BIS	Bureau of Indian Standards
SI	Sub-Index
CA	Cluster Analysis
FA	Factor Analysis
PCA	Principal Component Analysis
ML	Machine Learning
SRDD	Scottish Research and Development Department
NSFWQI	National Sanitation Foundation Water Quality Index
BAP	Budget Allocation Procedure
GIS	Geographic Information System
Na	Sodium
K	Potassium
Ca	Calcium
Cl^-	Chloride
F^-	Fluoride
NO_3^-	Nitrate
Mn	Manganese
Zn	Zinc
Fe	Iron
Ni	Nickel
Pb	Lead
Cr	Chromium
Cd	Cadmium

CHAPTER 1

INTRODUCTION

1.1 Overview

Water is one of the determinants of life here on Earth: it sustains human life, preserves ecosystems, and fosters economic development. The availability, quality, and management of water resources have impacts on the well-being of communities, the productivity of industries, and overall natural-environment health. Earth is a planet where 71% of its surface is covered by water, of which 97% of this is seawater (Musie & Gonfa, 2023). Since seawater is hardly available for human consumption, the world population has to rely on only 3% of freshwater, as indicated in the global water distribution. Of the available freshwater, only 0.06% can easily be accessed, and the remaining 99.94 % comprises the frozen polar ice cap, glaciers, and groundwater (Rijsberman, 2006). Lakes and rivers play a huge role in the global environment, acting as irrigation water sources, fish farming, shipping transport, and industrial and drinking water sources. Lakes and rivers hold 0.3% of the world's freshwater (El-Ghonemy, 2012). According to the study by Misstear et al. (2017), the irrigation sector uses only about 70% of the groundwater, and India, China, and the USA are the major leading countries in using this water source. Critical water quality issues include more than 2 billion people worldwide using sources of water contaminated with unsafe pathogens, while an estimated 4 billion lack access to safe drinking water without treatment (Biswas & Tortajada, 2019; Vega et al., 2018). Agricultural activities are responsible for the nutrient-rich runoff, which annually causes about 245,000 square kilometers of global waters to suffer from eutrophication and create hypoxic zones that decimate aquatic ecosystems (Karunanidhi et al., 2021; Tyagi et al., 2020). Industrial sources contribute to contamination because 30% of the world's available freshwater is used industrially and in municipalities, and generates by-products that include heavy metals as well as micropollutants, and over 1.5 billion people living in rural areas depend on unsafe groundwater, especially due to high levels of fluoride and arsenic (Schwarzenbach et al., 2010). Only about 10 percent of regions like South Asia receive proper treatment of wastewater, and this means pathogens and toxic substances end up in the supply of drinking water (Biswas & Tortajada, 2019; Vliet et al., 2021). India-based studies reveal that 26 percent of samples of water exceeded the safe fluoride level and thus would pose threats of fluorosis, especially to children (Karunanidhi et al., 2021). Even to date, untreated wastewater and agricultural runoff continue to cause pollution to millions of people, and it is estimated that up to 40 percent of the world's population suffers from severe water scarcity if considered both quality and quantity (Schwarzenbach et al., 2010; Vliet et al., 2021).

Most of the water used for rural and urban drinking sources comes from groundwater. Most of these sources are contaminated with fluoride, arsenic, and heavy metals, thus affecting millions of people (Sharma et al., 2017; Singh & Singh, 2002). More than 14.5 million people rely on water from this river in the Ganges basin, with a very high BOD all along, especially near some of the large urban cities like Calcutta, which has values of BOD ranging up to 5.95 mg/L due to untreated sewage (Sarkar et al., 2007). The waters of the Yamuna River, despite numerous restoration efforts, have remained under the "poor" rating for indices because of their high coliform bacteria and ammonia levels, indicating that efforts to regain potable standards continue to be a challenge (Sharma & Kansal, 2011). Even the Hindon River, Uttar Pradesh, is heavily polluted, with COD at 337.4 mg/L and BOD at 51 mg/L (Suthar et al., 2010). For instance, groundwater levels of irrigated areas such as Punjab, Rajasthan, and Tamil Nadu are reducing by 1-2 meters a year, and such a trend is likely to jeopardize future water security (Singh & Singh, 2002). At the per capita level, India's water availability is headed towards crossing 1,170 m^3/yr just above the water-stressed threshold, requiring urgent resolution through effective water management and control of pollution measures (Cronin et al., 2014).

Water quality monitoring is a highly challenging task since it heavily relies on a few parameters, such as pH, turbidity, DO, and TDS, demanding time-consuming and resource-intensive methods (Ahmed et al., 2020; Behmel et al., 2016). Worldwide, less than 40% of water bodies are adequately monitored, while 80% of wastewater released only indicates there are data gaps, mostly in poorer regions (Kirschke et al., 2020; Uddin et al., 2021). The introduction of new technologies, like the use of IoT-based monitoring systems, holds promises but is limited to very high initial costs, while access is only accessible to the more affluent countries of the world (Jan et al., 2021; Murray et al., 2022). Water quality's spatial and temporal variability increases the complexity since many monitoring programs cannot boast the resources needed to ensure complete coverage (Huang et al., 2021; Kachroud et al., 2019). Although Water Quality Indices have certainly made the interpretation of data easier, the outcome is generally afflicted by regional specificity that confines its applicability (Boyacioglu, 2007; Kachroud et al., 2019).

The Water Quality Index is an integrated measure that converts complex data on water quality into an easily understandable single numerical value, which gives a general judgment regarding suitability for specific use-drinking, agricultural purposes, or recreation (Kachroud et al., 2019). This index is primarily applied to monitor and better manage water quality. Thus, it simplifies the interpretation of environmental data for policymakers and stakeholders to act on (Boyacioglu et al., 2007). Calculation of WQI has many steps: selection of relevant water quality indicators such as pH, dissolved oxygen, and turbidity; assignment of weights according to the importance of each parameter; normalization of parameter values; and aggregation of these into a composite score by mathematical functions (Varadharajan, et al., 2009; Gupta & Gupta, 2021; Jha et al., 2015; Sun et al., 2016). BOD, nitrate levels, and TDS are the most frequently weighted upon expert judgment or statistical significance (Gupta & Gupta, 2021; Yidana & Yidana, 2010).

Some of the common issues in WQI models are uncertainty at every step, like the choice of parameters, derivation of sub-indices, weighting of parameters, and aggregation of the index (Oliveira et al., 2019; Uddin et al., 2021). Regional guidelines for selecting parameters are considered the most common restriction to the generalizability of WQI models. Overlapping parameters, such as dissolved oxygen and biochemical oxygen demand or turbidity and total solids, also skew the results, making them inaccurate in determining water quality (Oliveira et al., 2019; Patel et al., 2023). The WQI of some studies ranges from "good" at the upstream sites down to "poor" at the downstream due to the city's influence, where the values decrease by 11.6% in polluted areas (Gupta & Gupta, 2021; Kannel et al., 2007; Uddin et al., 2022). Improved ways, such as using a machine learning-based weight assignment, can address these issues and enhance the accuracy without losing ease of use (Gupta & Gupta, 2021; Uddin et al., 2022).

1.1.1 Water Quality Issues and Challenges in Madhya Pradesh

The water quality issues in Madhya Pradesh are alarming as there are high levels of industrial effluents, agricultural runoff, and improper waste management. Various studies have shown that most of the rivers, such as the Betwa, Chambal, Narmada, and Kalpi, have been saturated with a significant amount of pollutants. Industrial hotspots like Mandideep and Nayapura reportedly have higher levels of Biochemical Oxygen Demand (BOD) and Chemical Oxygen Demand (COD) compared to the permissible limit (Gupta et al., 2017; Verma et al., 2014; Vishwakarma et al., 2013). Groundwater in areas including Jabalpur and Rewa is contaminated with heavy metals such as chromium and has higher total dissolved solids and nitrates that make water undrinkable (Ghoderao et al., 2022; Mishra et al., 2012). Water from the Narmada River becomes more polluted during monsoon because it undergoes sedimentation and expands human-induced activities (Gupta et al., 2017). In addition, 25% of rural access to clean drinking water is reported in the Sagar and Indore zones of the region, and all districts have high positive rates of microbiological contamination (Godfrey et al., 2011;

Mishra & Nandeshwar, 2013). The overall water quality index (WQI) of many districts remains highly poor to unsuitable for consumption, attesting to the urgency required in formulating robust pollution control and sustainable water resource management strategies (Ghoderao et al., 2022; Gupta et al., 2017).

The water pollution level in Indore is highly critical, and significant contamination has been seen in both surface and ground sources. The Khan River is a major watercourse that is highly polluted due to untreated domestic and industrial discharges, which show BOD and COD at extremely high levels, often beyond permissible limits (Abhineet & Dohare, 2014; Dohare et al., 2018). Groundwater in urban areas is also contaminated with nitrates, fluorides, and heavy metals. Nitrate levels often exceed 45 mg/L, which is associated with agricultural runoff (Dohare et al., 2014; Sharma & Thakkar, 2014). The water source of the city depends mainly on the Narmada River and local reservoirs, and becomes turbid at levels of 1530 NTU during monsoons, making it unsafe even with treatment due to potential microbial pollution (Khadse et al., 2016). This important local water body, Sirpur Lake, suffers from eutrophication and microbial contamination with a high coliform count, which reflects fecal pollution (Nighojkar, & Chaurasia, 2017; Smruti & Sanjeeda, 2012). In addition, bacteriological analysis shows widespread contamination with pathogens like E. coli, meaning there is an urgent need for strict water quality management and public awareness campaigns (Smruti & Sanjeeda, 2012).

1.2 Motivation of the Study

Field surveys in five villages in the Indore district of Borkhedi, Gokanya, Harsola, Memdi, and Simrol revealed the urgent issues of water quality, such as high concentrations of fluoride, high organic and suspended loads. These problems are worsened by the lack of proper sanitation infrastructure and the absence of continuous and reliable systems of monitoring. The issue not only poses a risk to public health but also highlights a critical gap in rural water management. Existing Water Quality Index (WQI) models tend to miss region-specific pollutants or remain insensitive to changing field conditions. Inspired by these issues, this research performs a comparative evaluation of several WQI models to compare their accuracy, responsiveness, and context-specific appropriateness. The final objective is to determine models that are scientifically robust, operationally viable, and able to facilitate informed decision-making for sustainable water quality management in rural India.

Figure 1.1 Water Quality and Sanitation Challenges in Villages (Source: Me)

This scenario highlights the need for a systematic assessment of water quality and targeted interventions to ensure safe and sustainable water resources for these communities.

1.3 Scope of the study

The research focuses on assessing water quality in five selected villages of Indore through established WQI models. It addresses region-specific water contamination issues, including chemical contaminants such as fluoride and nitrates, and heavy metal contamination due to deficient sanitation facilities. The study underscores the need for regionally adaptive WQI models to address peculiar challenges at the rural level. It provides a comparative framework to evaluate the efficacy of various WQI models in varied environmental conditions. These findings can guide the sustainable management of water resources and policymaking in rural communities.

CHAPTER 2

LITERATURE REVIEW

2.1 WQI model structure:

2.1.1 Selection of parameters:

The selection of appropriate parameters is an important step in developing WQI, as it determines an index's effectiveness in showing water quality (Akhtar et al., 2021; Banda & Kumarasamy, 2020) as shown in Figure 2. Parameters typically chosen are physicochemical indicators like pH, turbidity, electrical conductivity, nitrates, and biological indicators like dissolved oxygen and fecal coliform (Aljanabi et al., 2021; Sutadian et al., 2016). They should represent the sources of pollution in the water body and the proposed water use, such as drinking, irrigation, industrial, etc. (Kumar et al., 2024; Sutadian et al., 2016). According to the study by (Sutadian et al., 2016), parameters for selection can be categorized into three distinct systems: fixed, open, and mixed.

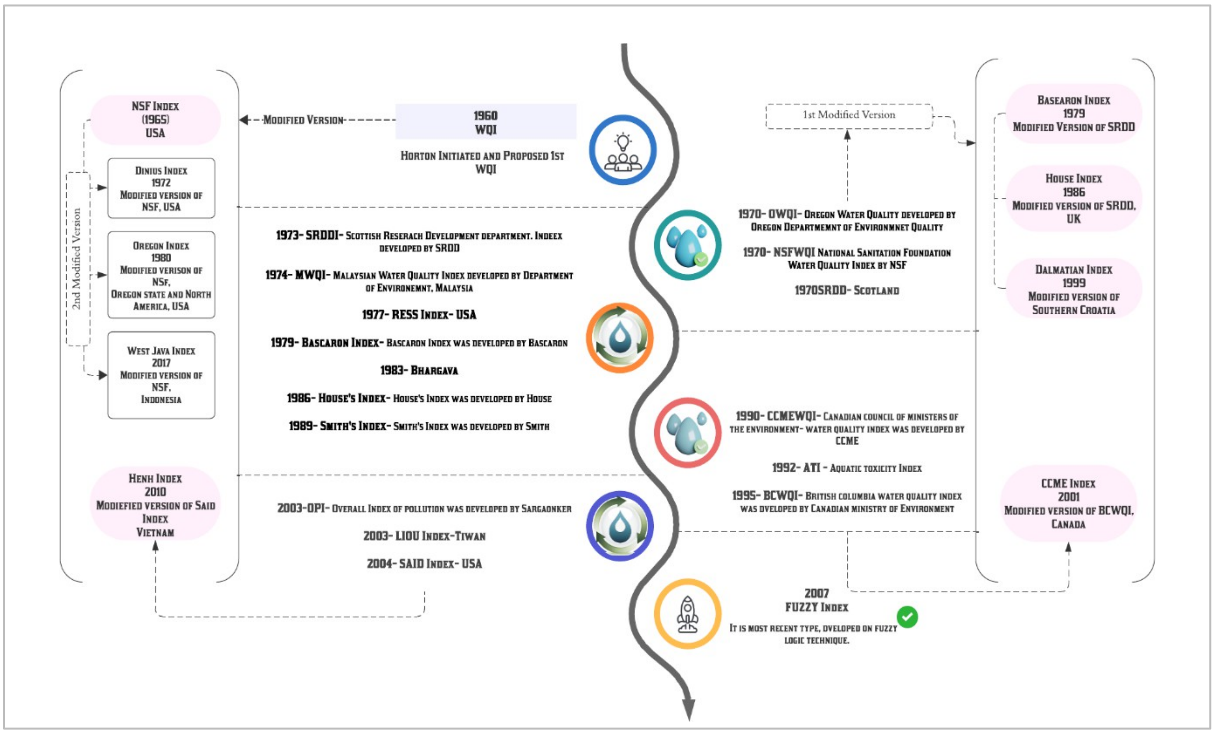

Figure 2.1 Historical development of the Water Quality Index models

Fixed system

The fixed system applies standardized and constant parameters used to compute WQI, making it uniform and comparable within and among regions and time. Common parameters include pH, DO, turbidity, and BOD, representing general water quality metrics (Akhtar et al., 2021; Kumar et al., 2024). This approach allows for a fair and objective assessment of water quality, but it can be ruthless because it does not take into consideration region-specific contaminants or emerging substances like heavy metals or microplastics (Patel et al., 2023; Terrado et al., 2010). For instance, the indexes such as the NSFWQI apply pre-set indicators. This approach ensures that the system is transparent and easy to use but is likely to neglect localized concerns over water quality (Kumar et al., 2024; Sutadian et al., 2016).

Open system

The open system allows for flexibility in that parameters are selected based on the nature of the water body, the use for which the water is intended, or regional issues. For instance, depending on the severity of industrial pollution in an area, consideration might be given to heavy metals or nitrates (Akhtar et al., 2021; Sutadian et al., 2016). The appropriateness and flexibility of this system mean that consistency in the assessments may not be achieved; hence, comparisons between regions become impossible (Sutadian et al., 2016; Terrado et al., 2010). Research has proved that open systems are most effective in areas of special ecological concerns or diverse uses of water, including irrigation, whether it is for agriculture or water supplies to an urban center, where parameter inclusion can differ drastically (Akhtar et al., 2021; Kumar et al., 2024).

Mixed system

The mixture of the fixed and open systems standardizes their compatibility as it couples the universal parameters core set. These universal parameters include, for example, parameters like pH and DO, which are complemented by additional parameters based on local environmental needs or emerging pollutants (Kumar et al., 2024; Patel et al., 2023). This means it ensures the consistency of assessment while at the same time ensuring comparability across regions. For instance, the Canadian Council of Ministers of the Environment Water Quality Index, CCME WQI, is a hybrid approach that can be applied suitably for changes requiring specific water-use requirements (Kumar et al., 2024; Terrado et al., 2010). It is really effective in those areas where the baseline quality of water should be evaluated along with some localized issues (Patel et al., 2023; Sutadian et al., 2016).

2.1.2 Formation of sub-indices:

One of the important stages in the WQI model structure is to form sub-indices, which transform individual water quality parameters into dimensionless values on one scale. Sub-indices reduce complex variability in water-quality data and make it easy to compare. It uses different approaches to generate sub-indices, ranging from linear interpolation-based, like in the case of the National Sanitation Foundation WQI (NSFWQI), to non-linear applications recommended in the Oregon WQI, which is well-suited for managing extreme values (Lumb et al., 2006; Neary et al., 2001a; Said et al., 2004). On the other hand, observations show that though most of the WQIs utilized a scale of 0 to 100 for the sub-indices, the weights and transformation functions were applied to control their sensitivities and reliabilities (Liou et al., 2004; Lumb et al., 2006). For example, the Canadian CCME WQI combines scope, frequency, and amplitude measures into sub-indices in an attempt to capture water quality trends, thereby allowing for clear communication among diverse stakeholders (Rosemond et al., 2009; Neary et al., 2001). The Bascaron model contains up to 26 parameters; for instance, a comprehensive water quality assessment is provided, but it increases the computational complexity (Uddin et al., 2021). Other approaches include Taiwan's Liou Index, which uses a combination of PCA and hybrid aggregation functions that balance the parameter-by-parameter influence with specific regional concerns (Liou et al., 2004). This practice of including biological and physicochemical indicators in forming sub-indices has gained significant importance in the global arena to improve the ecological relevance of WQIs (Lukhabi et al., 2023). Statistical validation, including principal component analysis and sensitivity tests, ensures that such sub-index transformations retain accuracy and sensitivity under various environmental conditions (Neary et al., 2001). Statistical studies have revealed that sub-index reliability depends greatly on adopting appropriate parameter thresholds that vary regionally and seasonally (Akhtar et al., 2021; Uddin et al., 2021). Out of the 35 world reviews, a global survey by (Akhtar et al., 2021), an overwhelming 82% of WQI models adopted sub-indices for rivers, lakes, and estuaries, while the remaining focused on groundwater and wetlands.

Any WQI model is essentially supported by sub-indices that convert complex parameter data into concise and interpretable scores that allow for strong assessments of water quality at multiple temporal and spatial scales (Lukhabi et al., 2023; Lumb et al., 2006; Said et al., 2004). The following methods are commonly employed in the development of sub-index functions:

- **Expert judgments**
- **Statistical Techniques**
- **Factor Analysis (FA)**
- **Cluster Analysis (CA)**
- **Use of Water Quality Standards**

Expert judgments:

Expert judgment is one of the key methods that have been used in determining sub-indices for water quality index models, especially where scientific data is limited, vague, or regionally specific. In such a case, the approach relies on the experience and opinion of water quality experts in establishing parameter importance, methodologies for scaling, and aggregation sub-indices. For instance, a Delphi study with 142 water quality experts concluded by finalizing 11 critical parameters from a list, which included pH, dissolved oxygen, and turbidity, with an absolute global relevance yet localized adaptation (Horton et al., 1965; Sutadian et al., 2016). Expert panels also provided feedback through several rounds of iteration, with improvements to the curves of sub-indices to gain consensus on the extent of quality variation derived from fluctuations in parameters (Banda & Kumarasamy, 2020; Horton et al., 1965). Techniques like AHP are combined with expert elicitation to arrive at weights systematically applied to parameters for the WQI to reflect practical and ecological priorities (Deininger, 1980; Steurer, 2011). Statistical verifications, including consistency ratio checks, have been applied to assure reliability in scales and weightings derived from experts (Banda & Kumarasamy, 2020; Deininger, 1980). Studies indicate that by basing models on expert judgment, such as Bascaron and Liou indices, they have gained higher sensitivities to changes in pollutants and are more fit for complicated, multi-parameter scenarios (Steurer, 2011; Sutadian et al., 2016). Second, anonymous elicitation methods used in the Delphi method help avoid groupthink and biases because experts can objectively revise their inputs independently (Deininger, 1980; Steurer, 2011). The empirical data is balanced with professional insight here to ensure the WQI is equally robust from a scientific standpoint and implementable practically across various environmental and policy frameworks.

Statistical Techniques:

Applying statistical techniques to build sub-indices for WQI models transforms raw data into standardized metrics to effectively assess water quality. These techniques include regression analysis that forms relationships between water quality parameters, such as nutrient levels, with algal growth, which mostly have high correlation coefficients- $R^2 > 0.85$ with adequate predictive power (Dutta et al., 2018; Ghesquière et al., 2015). Correlation analysis identifies interdependencies among parameters such as pH, dissolved oxygen (DO), and total suspended solids (TSS), which streamlines the selection of key indicators for sub-indices (Shil et al., 2019; Silva et al., 2021). Weighted methods allow assigning significance to parameters according to the variability in the data and through expert knowledge; hence, factors such as turbidity and nitrates are usually given more importance (Nagaraju et al., 2016; Shil et al., 2019). Advanced techniques, such as the temporal and spatial discriminant analysis, can elevate the accuracy of sub-index generation since they determine seasonally or regionally changing parameters that explain significant water quality alterations (Mamun & An, 2021; Varol, 2020).

Geospatial tools, like Kriging and statistical processing, can produce spatial distribution maps of water quality indicators, making it easier for people to identify trends and pinpoint hotspots of pollution (Masood et al., 2022; Silva et al., 2021). Descriptive statistics allow for the establishment of base values in parameter variability; normalization techniques allow for standardization and comparability across different datasets (Dutta et al., 2018; Nagaraju et al., 2016). Validation through techniques such as Mann-Kendall trend tests ensures that the sub-index transformations are still robust under temporal and environmental variability (Mamun & An, 2021; Varol, 2020). The statistical methods used enhance the sub-indices' reliability, accuracy, and interpretability. The sub-indices are strongly necessary for applications in WQI models across dynamic and diverse water quality scenarios. Given their ability to describe multidimensional datasets succinctly, they can provide useful insights for water resource management and policy formulation.

Factor Analysis (FA):

Factor analysis is another critical statistical technique applied in multivariate analysis, which is used to form sub-indices in WQI models. It applies the concept of grouping water quality parameters into various factors to identify the underlying relationships among those parameters and reduce the dimensionality of the data while retaining the variance. For example, in the Carson Valley in Nevada, Factor Analysis was applied to 10 pollutant parameters and was successfully reduced to two principal indices with 99% reliability using an F-test ($R^2 = 0.9754$) (Joung et al., 1979). Similarly, in the Ganga River, Factor Analysis effectively grouped parameters like Dissolved Oxygen (DO), pH, and Total Dissolved Solids (TDS), explaining over 80% of the total variance and reducing parameters from 28 to 9 (Tripathi & Singal, 2019a, 2019b). This technique helps attach weights to parameters by finding their relative contribution to the overall water quality. For example, weights computed through Factor Analysis on Turkish surface waters led to the development of an Ecological Water Quality Index, which ensured that at least one parameter was taken from each factor class (Boyacıoglu & Boyacıoglu, 2020). Another example is its use in Rhodes Island, Greece, where Factor Analysis aggregated critical parameters like nitrates, sulfates, and conductivity, simplifying the WQI development process (Alexakis, 2022). The results of Factor Analysis can be statistically validated using measures such as the Kaiser-Meyer-Olkin (KMO) measure (>0.5 for sampling adequacy) and Bartlett's Test of Sphericity ($p < 0.05$ for significant correlations) (Tripathi & Singal, 2019; Varol & Davraz, 2015). Rotation methods, such as Varimax, help to make the interpretation of the parameter loadings easier. In Nile River pollution studies, Factor Analysis determined the important sources of pollution to be agricultural runoff and industrial effluent, while accounting for more than 75% of the variability in water quality (Yousry & Gammal, 2015). One of the powerful tools in forming WQI is factor analysis, as it offers an objective basis for parameter selection, weight assignment, and pollution source identification, thus improving the scientific robustness and applicability of water quality assessments. (Gulgundi & Shetty, 2018) utilized PCA to assess the correlation among weighting parameters, as illustrated in Equation (2.1).

$$Z_{ij} = a_{i1}x_{j1} + a_{i2}x_{j2} + a_{i3}x_{j3} \ldots + a_{im}m_{jm} \tag{2.1}$$

Where, Z = component score

x = the estimated variable value

i = the component number

j = the sample number

a = the loading component

m = the total number of variables.

Cluster Analysis (CA):

Cluster Analysis (CA) is a well-established statistical method that groups similar data points into clusters to draw patterns or trends from complex datasets in water quality. CA plays a crucial role in WQI model sub-index formation, as it is necessary for the classification of water quality parameters, monitoring sites, and seasonal variations. Data standardization is the initial step prior to clustering, which standardizes the parameters measured in different units. Distance metrics like Euclidean or Manhattan distances are often used to measure similarity between the data points, whereas hierarchical methods such as Ward's linkage or k-means clustering are used to determine clusters. In the context of the Godavari River, CA identified 34 monitoring stations into three groups, namely, less polluted, moderately polluted, and highly polluted, based on which focused monitoring efforts could be made (Gupta et al., 2015). Secondly, the Mekong Delta study classified water quality into four clusters according to key parameters such as Total Suspended Solids (TSS) and coliform counts and exploited seasonal and spatial variability (Giao & Nhien, 2021). CA not only helps reduce dimensionality but also optimizes the monitoring network. For example, New Zealand showed how CA effectively categorized 680 groundwater sites into representative clusters to streamline its monitoring efforts while maintaining its data integrity (Daughney et al., 2012). The method's ability to merge interval-valued data, demonstrated in the assessment of the Huaihe River, results in no information loss while obtaining clusters, thus further enhancing data accuracy and reliability (Shan et al., 2021). Validation techniques such as the Corrected Rand Index (CRI) are commonly used to validate the soundness of the clustering results. The strength of this technique is its ability to consider various parameters so that the whole spectrum of water quality changes across time and space can be represented.

Use of Water Quality Standards:

Sub-indices for WQI can be developed based on water quality standards, as standards offer universally or regionally accepted standards for various parameters. Regulation-oriented bodies, such as WHO, EPA, or regional bodies, define limits of permissible quantities for various key parameters of water quality, such as pH, dissolved oxygen, nitrates, and heavy metals. For example, in investigations of the Tigris River, standards were the linchpin to transforming raw information into meaningful index values; the standards conformed to international standards for potable water quality (Abed et al., 2022). Likewise, WQI Vietnam used national standards for the allowable concentrations of chemicals, thereby ensuring the index reflected the region's environmental conditions (Van et al., 2022). The CCME WQI, widely referenced worldwide, based on the three-factor approach, correlates scope, frequency, and amplitude to the standards set, thus providing a flexible yet robust framework (Banda & Kumarasamy, 2020b). In South Africa, compliance with groundwater quality standards allowed the classification of water resources into suitability classes for domestic use (Nzama et al., 2021). Statistical analysis showed that it standardizes data interpretation while enhancing indices' comparability across regions, as shown in 80% of global WQI applications (Akhtar et al., 2021; Kumar et al., 2024). In addition, standards ensure indices reflect the actual environmental and health risks, as any deviation from permissible limits is directly proportional to the degree of severity of the indicated pollution. As seen in Brazil's aquifer studies, the integration of standards highlighted deficiencies in treatment infrastructure when groundwater consistently failed to meet basic potability levels (Sabino et al., 2024). Moreover, sub-index functions calibrated against these benchmarks, such as linear or non-linear transformations, align parameter values with acceptable risk thresholds, offering insight into resource quality (Sutadian et al., 2016). Across studies, standards provided a basis for developing indices that are not only scientifically valid but also socially relevant, thus allowing policymakers to rank interventions appropriately. This synergy between scientific rigor and practical utility underscores the centrality of water quality standards in crafting meaningful WQI models.

2.1.3 Parameter weighting:

Parameter weights assignment is important in WQI development since they display the relative significance of water quality parameters and influence the index score. Weights could be either equal, in which case all the parameters are treated equally important, or unequal, where weights are assigned per the importance of each parameter or specific water quality guidelines (Sarkar & Abbasi, 2006). Unequal weights are often encountered in WQI models like the Horton, Bascaron, and Almeida indices, which apply weights with integer values and whose summation exceeds 1. In contrast, the Oregon index assigns equal weights to all parameters, while others, such as CCME, Smith, and Dojlido indices, do not apply parameter weights at all. The use of unequal weighting systems enhances the robustness of a WQI model, which in turn diminishes uncertainty and maximizes accuracy. The Delphi technique and the Analytical Hierarchy Process (AHP) are widely adopted in methods for determining weights (Mogane et al., 2023).

Delphi method:

The Delphi method is a group of expert panels comprising stakeholders like policymakers and water quality experts, presenting their consensus-based weights through interviews, questionnaires, and discussions. For instance, (Horton et al., 1965) and (Brown et al.,1970) applied this method to enhance the credibility of parameter weights in different indices. (Horton et al., 1965) developed parameter weighting as part of WQI development; assigned weights as four parameters (specific conductivity, chlorides, alkalinity, carbon chloroform extract) were assigned one each; two for one parameter (coliform); and four for the remaining three, namely dissolved oxygen, sewage treatment, and pH. (Brown et al.,1970) further developed this approach using a large panel of water quality experts from the USA to add objectivity and credence. Specialists graded relative parameters of water quality on a scale from 1 (most significant) to 5 (least important). The arithmetic mean was then calculated for the experts' ratings, and the parameter with the highest rating for significance was assigned a temporary weight of 1.0. Other parameters were assigned temporary weights based on the highest rating divided by the respective mean rating. The temporary weights were normalized by dividing each by the total sum of weights, thus ensuring that the summation of all parameter weights equalled 1. Since then, the Delphi method has been widely applied in various WQIs to establish relative parameter weights and maintain consistency in the weighting process through expert consensus(Sutadian et al., 2016).

Analytical Hierarchy Process (AHP):

Saaty developed AHP in the 1970s. It uses pairwise comparisons to derive parameter weights by integrating qualitative and quantitative inputs. In this approach, weight assessment is accomplished through pair-wise comparison matrices in which the respondents, either experts or the public, are asked to give their preference by comparing several choices. (Sutadian et al., 2016),(Ocampo-Duque et al., 2006), and (Gazzaz et al., 2012) studied how AHP can reduce uncertainty and improve weighting accuracy. A study by (Gazzaz et al., 2012) mentioned that AHP reduces uncertainty and increases consistency by adopting a consistency ratio to check on the legitimacy of the weight assignment process. For instance, West Java WQI has been practiced as it was used to rank five key parameters (Sutadian et al., 2016). (Ocampo-Duque et al., 2006) successfully applied AHP to combine five groups of similar parameters into weights that accurately reflected their ecological significance. The methodology incorporates expert opinions and ensures reliability through sensitivity analysis, enhancing the WQI models' robustness. AHP further eliminates biases since it has been in direct contact with stakeholder involvement when used to prioritize environmental and human health-related parameters (Ocampo-Duque et al., 2006; Sutadian et al., 2016).

Though equal weights are usually preferred due to the simplicity of the approach and to be free from subjective biases, unequal weights are imperative for applications emphasizing specific water uses, including protection of drinking water safety or ecological health. If improper weights are chosen, the index may become skewed as the less significant parameters get overemphasized. The Participatory methods, such as the Budget Allocation Procedure (BAP) and Simos' modified procedure, are less practiced but still provide practical remedies to overcome the weighing limitations (Kodikara et al., 2010). Finally, careful proper weighing according to the judgment of experts or water quality standards will ensure good and reliable WQI models for all applications in water resource management.

2.1.4 Aggregation function:

Aggregation is a common final process in WQI development, where the parameter sub-indices are summed up into a solitary WQI score (Sutadian et al., 2016). This step typically involves mathematical calculations of sub-indices based on their assigned weights and finally provides a comprehensive score to represent overall water quality. Aggregation can be staged sequentially if sub-indices need to be aggregated before their aggregation results in the final index value. Most often used aggregation functions are additive or arithmetic and multiplicative or geometric; besides, some of the other less frequent aggregation functions are the minimum operator and the harmonic mean of squares (Akhtar et al., 2021; Kumar et al., 2024; Patel et al., 2023; Uddin et al., 2021). Additive aggregation is carried out through weighted or unweighted summation, while Multiplicative aggregation accounts for the parameters' interdependence. The selected approach varies based on the precision level needed and whether the parameters are equally or unequally weighted (Abbasi & Abbasi, 2012). This aggregation step is critical because it condenses various water quality parameters and condenses them into a single-digit WQI, simplifying the interpretation and decision process. Variants of these approaches are also used in some models for greater flexibility and adaptability. Finally, the aggregation process combines all sub-index values to fully represent water quality, thus clarity and usefulness for the stakeholders. The different aggregation functions are discussed briefly here.

Additive functions:

Various WQI models, including the Horton model, the SRDD model, the House index, Malaysian and Dalmatian index models, employed a simple additive aggregation function given by:

$$WQI = \sum_{i=1}^{n} s_i w_i \qquad (2.2)$$

In the above equation (2.2),

s_i = the sub-index value for parameter i

w_i = i^{th} parameter weight value (which ranges from 0 to 1).

n = the total number of parameters.

Multiplicative functions:

Some index models used the multiplicative function for aggregation and can be expressed as:

$$WQI = \prod_{i=1}^{n} s_i^{w_i} \qquad (2.3)$$

In the above equation (2.3),

s_i = the sub-index value for parameter i

w_i = i^{th} parameter weight value (which ranges from 0 to 1).

n = the total number of parameters.

Combined aggregation functions:

The final WQI score has been derived using combined aggregation methods, where additive and multiplicative functions are combined, by various researchers ((Abbasi & Abbasi, 2012; Swamee & Tyagi, 2000)). The application of such methodology has been followed with remarkable success by (Liou et al., 2004), (Alobaidy et al., 2010), and (Ewaid & Abed, 2017) for the assessment of Taiwan's water quality. Another major model is the NSF, which integrates both additive and multiplicative functions into its structure and shows how this approach of combining these functions effectively captures the complexity involved in assessing water quality.

Square root of the harmonic mean functions:

The square root of the harmonic mean function is a numerical technique applied to aggregate parameters or sub-indices in some WQI. The method uses the harmonic mean for averaging and takes the square root for the final computation. This method emphasizes low values in the data set, which is preferable if the worst parameter determines the overall score. The function can be formulated as,

$$WQI = \sqrt{\frac{n}{\sum_{i=1}^{n} s_i^{-2}}} \tag{2.4}$$

In the above equation (2.4),

s_i = the sub-index value for parameter i

n = the total number of parameters.

Minimum operator function:

(Smith, 1989) proposed the minimum operator function, as shown in Eq (5), the overall water quality index score is determined by taking the minimum sub-index of the parameters developed specifically for rivers and streams to assess New Zealand's water quality. After some time, (Shah & Joshi, 2017) applied the Smith index for assessing surface water quality in India, marking the first application of the Smith index in the Sabarmati River, Gujarat (India), though it was initially recommended to apply it only in New Zealand. The mathematical expression of the minimum operator function is,

$$WQI = Min(s_1, s_{i+1}, s_{i+2}, \ldots, I_{sub_n}) \tag{2.5}$$

In the above equation (2.5),

s_i = the sub-index value for parameter i

n = the total number of parameters.

Unique linear/non-linear aggregation functions:

Few WQI models have used specific linear or non-linear aggregation functions to calculate the final index value. A more interesting example is the Said index, as presented by (Said et al., 2004), in which the parameter concentrations are directly used as sub-index values, and a unique logarithmic aggregation function is applied. This concept introduces the parameter concentrations into the computation of the final WQI, creating a new pathway for water quality evaluation. The mathematical expression of the function is,

$$WQI = \log\left[\frac{(DO)^{1.5}}{(3.8)^{TP}(Turbi)^{0.15}(15)^{\frac{fecal}{10000}} + 0.14(SC)^{0.5}}\right] \tag{2.6}$$

In the above equation (2.6),

DO = sub-index values for dissolved oxygen (% oxygen saturation)

Turbi = turbidity (nephelometric turbidity units [NTU])

TP = total phosphates (mg/L)

fecal = fecal coliforms (counts/100 mL) & SC = specific conductivity (S/cm at 25 ◦C)

2.2 Literature Gap

Water Quality Index (WQI) studies are confronted by several key gaps, where no conventional framework of parameter selection exists, resulting in inconsistency and the loss of emerging pollutants and heavy metals. Available aggregation methods, mainly additive and multiplicative, oversimplify the interaction among parameters, requiring the creation of sophisticated probabilistic as well as hybrid models. Although predictive accuracy is enhanced through AI and ML, data limitation, computational intensity, and the absence of field validation remain challenges. In particular, no study provides a thorough framework to identify appropriate models of WQI for urban and rural settings, further confining their utility in the real world. Industrial, irrigation, and aquatic ecosystem appraisal indices also lack methodological standardization. Model validation is a significant lacuna since sensitivity analysis, uncertainty assessment, and independent validation data are hardly ever integrated. This study first attempts to develop a comparison among models of the Water Quality Index applied exclusively to the rural villages of Indore. The research thus draws attention to the region-specific issues in chemical and heavy metal contamination, which demand tailored WQI models. It bridges the long-reproached gap in the methodologies applied to assess the water quality in a rural context.

CHAPTER 3

MATERIALS AND METHODS

3.1 Methodological Flow Diagram

The Water Quality Index (WQI) assessment methodology follows a well-organized procedure, as shown in Figure 3.1. This is initiated with a literature review of WQI to appreciate the prevailing frameworks, then proceeds to problem identification and research gap identification. The selection of parameters includes incorporating the appropriate physicochemical and heavy metal parameters. Objectives of the study are:

i. To assess physico-chemical water quality parameters and heavy metals in five villages (Simrol, Memdi, Borkhedi, Gokanya, Harsola).

ii. To calculate the weightage of every parameter using AHP.

iii. Comparative Assessment of Water Quality Index Models using modified calculated weightage and Entropy weighted WQI for Rural Water Evaluation.

iv. To do a Sensitivity Analysis of Water Quality Models.

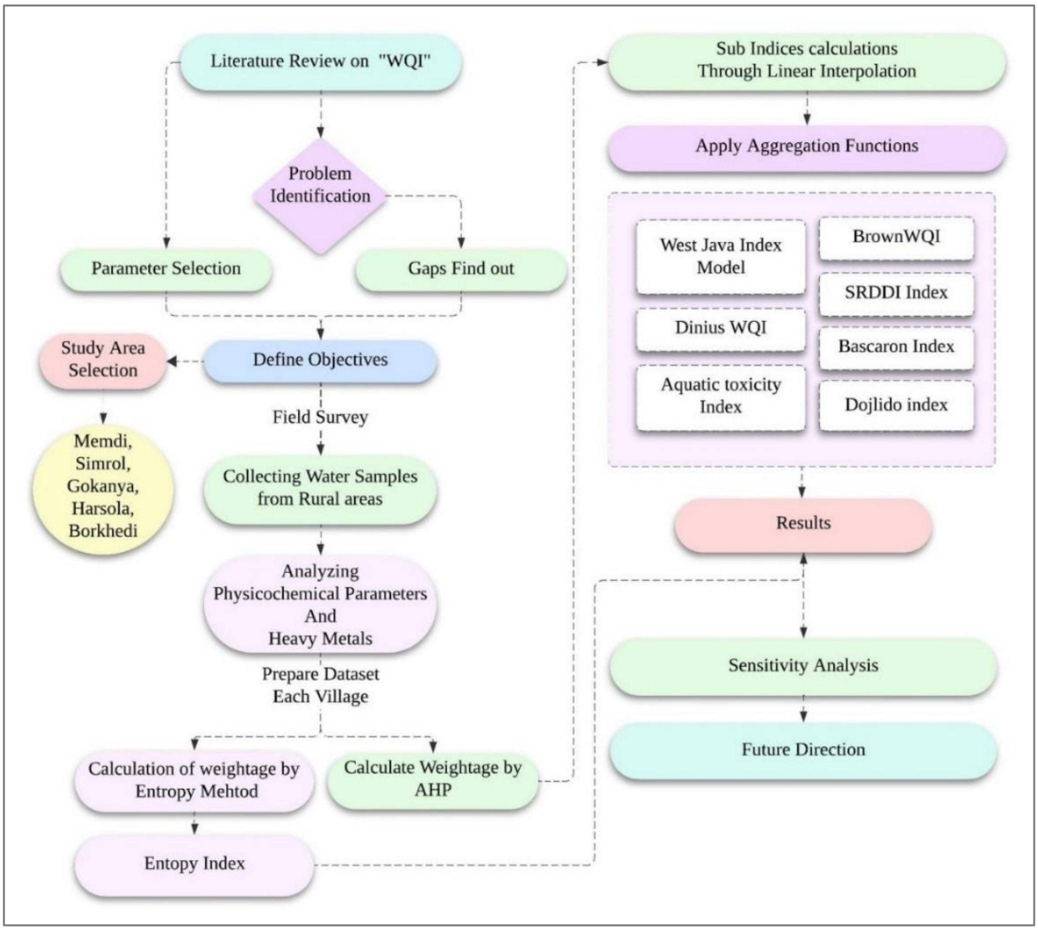

Figure 3.1 Study Flow Chart

Study sites are chosen, and Memdi, Simrol, Gokanya, Harsola, and Borkhedi are chosen as field surveys are made to obtain water samples from rural freshwater sources. Thereafter, a comprehensive analysis of physicochemical parameters and heavy metal concentration was conducted through prescribed APHA methods for every village. Two parallel weightage approaches are applied to the water quality parameters, one using the Analytic Hierarchy Process (AHP) and the other through the Entropy method. The water quality parameters are used to calculate sub-indices through linear interpolation. Subsequently, various aggregation functions corresponding to different WQI models, such as Brown, SRDDI, Bascaron, Dinius, West Java, Aquatic Toxicity, and Dojlido index, are applied to derive composite WQI scores. The outcomes are analyzed to interpret spatial and model-specific trends, followed by a sensitivity analysis to identify the most influential parameters. The research concludes with the formulation of future directions for more adaptive and region-specific water quality monitoring tools.

3.2 Study area

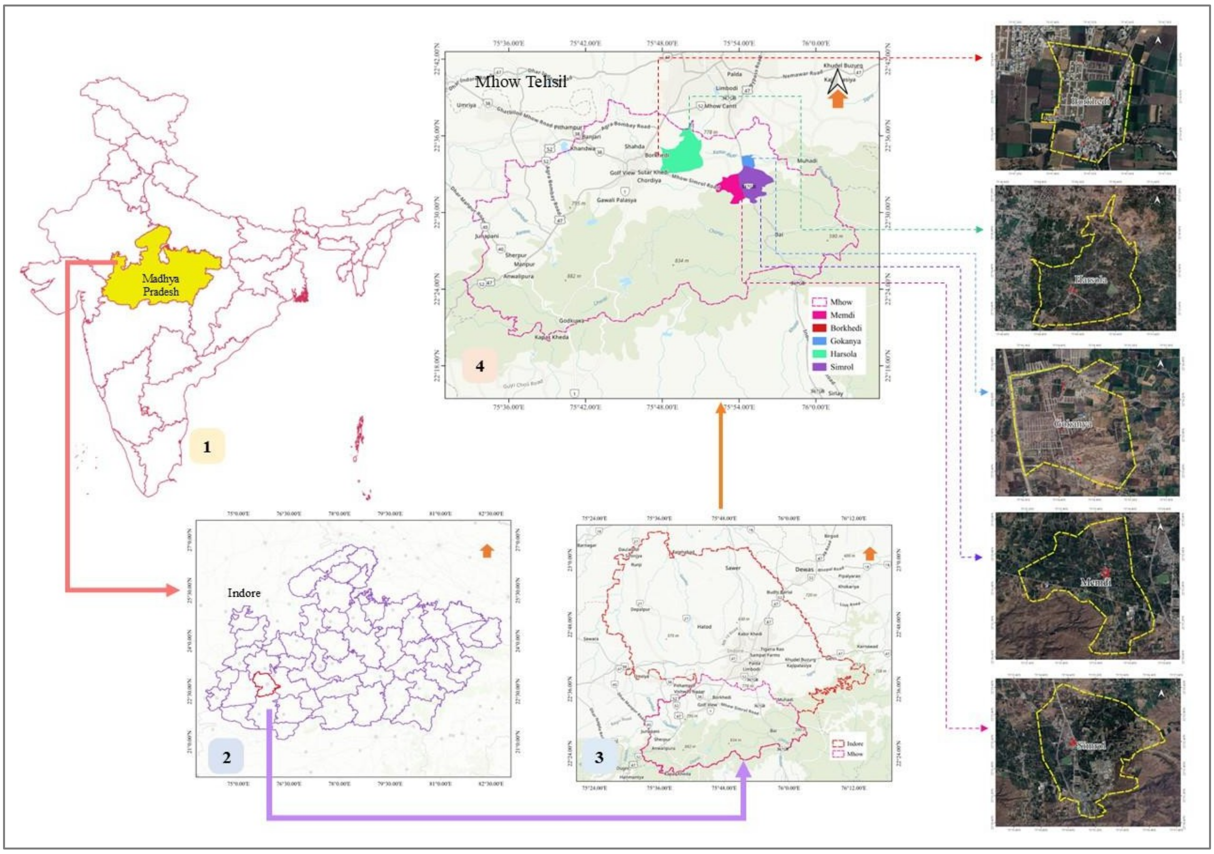

Figure 3.2 Study Area

The study was carried out among five selected villages in Madhya Pradesh, India, namely Simrol (22.6763° N, 75.7333° E), Memdi (22.6842° N, 75.7747° E), Borkhedi (22.6533° N, 75.7117° E), Gokanya (22.6874° N, 75.8271° E), and Harsola (22.6828° N, 75.7884° E). All the villages come under the Mhow Tehsil of Indore District, located in Madhya Pradesh State, belonging to India.

3.3 Sample collection and analysis

A total of 36 water samples were collected from five villages of Indore district that were identified for sampling: Gokanya (G1-G6), Simrol (S1-S6), Memdi (M1-M8), Harsola (H1-H8), and Borkhedi (B1-B8), as shown in Table 3.1.

Table 3. 1 Sample Locations of all Villages

Sample	Description	Longitude	Latitude
G1	School tap water	75.911	22.572
G2	Borewell (near the primary school)	75.91	22.572
G3	Borewell	75.911	22.571
G4	Handpump	75.913	22.562
G5	Handpump	75.913	22.561
G6	Borewell	75.91	22.566
S1	Borewell	75.912	22.54
S2	Handpump	75.911	22.541
S3	Borewell	75.911	22.539
S4	Handpump	75.912	22.54
S5	Borewell	75.911	22.539
S6	Borewell	75.912	22.539
M1	Handpump	75.893	22.535
M2	Borewell	75.894	22.535
M3	Borewell (near farmland)	75.894	22.534
M4	Borewell	75.893	22.534
M5	Borewell (near school)	75.892	22.534
M6	Handpump	75.893	22.535
M7	Handpump	75.892	22.533
M8	Borewell	75.893	22.533
H1	Handpump	75.817	22.571
H2	Handpump	75.818	22.57
H3	Handpump near school	75.818	22.569
H4	Tap water	75.817	22.57
H5	Tap water	75.816	22.57
H6	Borewell	75.815	22.57
H7	Borewell (near farmland)	75.819	22.569
H8	Borewell	75.82	22.567
B1	Borewell	75.792	22.578
B2	Handpump	75.792	22.574
B3	Borewell	75.793	22.576
B4	Borewell	75.793	22.574
B5	Tubewell	75.792	22.574
B6	Borewell	75.792	22.573
B7	Borewell	75.79	22.575
B8	School tap water	75.794	22.577

The sampling was conducted using grab sampling method to collect major rural freshwater sources like handpumps, tubewells, and surface water bodies. All samples were retrieved in pre-cleaned 1-litre polyethylene bottles, which were rinsed three times with the corresponding source water to prevent cross-contamination. After collection, samples were put immediately in insulated iceboxes and stored at 4°C to maintain their physicochemical integrity until analysis. This handling method complies with the Standard Methods for the Examination of Water and Wastewater (APHA, 2017) to ensure method consistency. The analyses were performed at the *Environmental Engineering Laboratory, IIT Indore*. All physicochemical and heavy metal parameters were determined under controlled laboratory conditions. Standard solutions and blanks for reagents were made before every batch of tests to calibrate equipment and ensure accuracy. To ensure analytical precision and reproducibility, all tests were performed in triplicate. The parameters analyzed include:

(a) **Physicochemical indicators:** pH, turbidity (NTU), free chlorine, alkalinity, hardness, electrical conductivity (EC), dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS), volatile suspended solids (VSS), nitrate, fluoride, and chloride.

(b) **Heavy metals and ions**: Manganese (Mn), Zinc (Zn), Iron (Fe), Nickel (Ni), Cadmium (Cd), Lead (Pb), Sodium (Na), Potassium (K), Calcium (Ca), and Chromium (Cr).

The analytical methods and instruments used for each water quality parameter are detailed in Table 3.2, ensuring standardized and accurate measurements as per APHA guidelines.

Table 3. 2 Instrumentation and Analytical Methods Used for Water Quality Parameter Analysis

Parameter	Method Used	Instrument Name	Company	Model No.
Alkalinity	Titration Method	Burette, Conical flask	Omsons	—
Biochemical Oxygen Demand (BOD)	5-Day Incubation	Incubator	Kay Pee Udyog	KL-103-0
Cadmium (Cd)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Calcium (Ca)	Flame Photometry	Flame Photometer	YA-SAN(INDIA)	—

Chemical Oxygen Demand (COD)	Closed Reflux Colorimetric Method	COD Analyzer	Hanna Instruments	HI839800
Chloride	Titration Method	Burette, Conical flask	Omsons	—
Chromium (Cr)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Dissolved Oxygen (DO)	DO Meter	DO Meter	Lutron	DO-5509
Electrical Conductivity (EC)	Research-grade benchtop meter	Research-grade benchtop meter	Hanna Instruments	HI5522
Fluoride	photometer	HR Fluoride Portable Photometer	Hanna Instruments	HI97739
Free Chlorine	photometer	EPA Compliant Benchtop Turbidity and Chlorine Meter	Hanna Instruments	HI83414
Hardness	Titration Method	Burette, Conical flask	Omsons	—
Iron (Fe)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Lead (Pb)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Manganese (Mn)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Nickel (Ni)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—
Nitrate	photometer	Nitrate Photometer	Hanna Instruments	HI97728
pH	Research-grade benchtop meter	Research-grade benchtop meter	Hanna Instruments	HI5522
Potassium (K)	Flame Photometry	Flame Photometer	YA-SAN(INDIA)	—

Sodium (Na)	Flame Photometry	Flame Photometer	YA-SAN(INDIA)	—
Total Kjeldahl Nitrogen (TKN)	Kjeldahl Digestion Method	Kjeldahl Apparatus	Pelican Equipment	SUPRA-LX
Total Suspended Solids (TSS)	Gravimetric Method	Hot Air Oven	Kay Pee Udyog	KL-103-0
Turbidity	Nephelometric Method	EPA Compliant Benchtop Turbidity and Chlorine Meter	Hanna Instruments	HI83414
Volatile Suspended Solids (VSS)	Gravimetric Method	Muffle furnace	Kay Pee Udyog	KL-103-0
Zinc (Zn)	AAS	Atomic Absorption Spectrophotometer	Motras Scientific	—

3.4 Formation of sub-indices:

Sub-index (SI) transformation is a fundamental element in Water Quality Index (WQI) models, whereby the recorded values of the water quality parameters are transformed into dimensionless scores, usually on a scale from 0 to 100, with 0 indicating the worst and 100 the best water quality. This process is vital for normalizing varied parameter units to a common scale. Different approaches have been utilized to obtain SI values, as elaborated in works by (Sutadian et al., 2016; Uddin et al., 2021). Most WQI models apply interpolation methods based on regulatory threshold limits (e.g., WHO, BIS, CPCB) to calculate sub-indices; however, some models apply the raw indicator values directly without normalization (Uddin et al., 2021). Linear interpolation rescaling functions suggested by (Uddin et al., 2022) (see Equations (3.1) – (3.3)) were utilized in this study to rescale raw measurements to SI values based on the guideline limits shown in Table 3.3. The respective SI calculation framework, as illustrated in Table 3.2, represents how these equations are utilized for various water quality parameters.

$$SI = (SI_u - SI_l) - \frac{(SI_u \times WQ_m)}{(STD_u - STD_l)} \tag{3.1}$$

$$SI = SI_u \times \frac{(WQ_{im} - STD_l)}{(STD_u - STD_l)} \tag{3.2}$$

$$SI = (SI_u - SI_l) - \frac{(WQ_{im} - STD_l)}{(STD_u - STD_l)} \times SI_u \quad (3.3)$$

SI_l = the Lower Limit of the possible SI value

SI_u =the Upper Limit of the possible SI value

STD_l= Lower Threshold value of the Water Quality Standards

STD_u= Upper Threshold value of the Water Quality Standards

WQ_m = Measured parameter value

Table 3. 3 Standard limits for Water quality parameters

Parameters	Unit	Acceptable Limit	Permissible Limit	Standards
pH	_	6.5-8.5	No relaxation	BIS (IS 10500-2012)
Turbidity	NTU	1	5	BIS (IS 10500-2012)
Free Chlorine	mg/L	0.2	1	BIS (IS 10500-2012)
Alkalinity	mg/L	200	600	BIS (IS 10500-2012)
Hardness	mg/L	200	600	BIS (IS 10500-2012)
DO	mg/L	>6	-	CPCB
BOD_5	mg/L	< 2	No relaxation	CPCB
COD	mg/L	Not specified	Not specified	BIS (IS 10500-2012)
TSS	mg/L	Not specified	Not specified	BIS (IS 10500-2012)
VSS	mg/L	Not specified	Not specified	BIS (IS 10500-2012)
Mn	mg/L	0.1	0.3	BIS (IS 10500-2012)
Zn	mg/L	5	15	BIS (IS 10500-2012)
Fe	mg/L	0.3	No relaxation	BIS (IS 10500-2012)
Ni	mg/L	0.02	No relaxation	BIS (IS 10500-2012)
Cd	mg/L	0.003	No relaxation	BIS (IS 10500-2012)
Na	mg/L	200	-	WHO (1984)
K	mg/L	200	-	WHO (1984)
Ca	mg/L	75	200	BIS (IS 10500-2012)
Cr	mg/L	0.05	No relaxation	WHO
Pb	mg/L	0.01	No relaxation	BIS (IS 10500-2012)
EC	µS/cm	-	500	WHO (1984)
Fluoride	mg/L	1	1.5	BIS (IS 10500-2012)
Chloride	mg/L	250	1000	BIS (IS 10500-2012)
Nitrate	mg/L	45	No relaxation	BIS (IS 10500-2012)

3.5 Parameter weighting:

Weights for parameter assignment are an important part of the process of creating Water Quality Index (WQI) models since they indicate the relative importance of individual parameters with respect to their impact on total water quality. In this research, the Analytic Hierarchy Process (AHP) was utilized for weights assignment and provides a systematic, multi-criteria decision-making method. AHP facilitates the systematic ranking of water quality parameters based on their relative importance to one another in relation to suitability for drinking water. The AHP methodology was executed using *Microsoft Excel 2021*, wherein a pairwise comparison matrix was constructed, and consistency ratios were calculated to validate the reliability and consistency of the assigned weights. Parameters with greater significance to human health were given larger weights because of their toxicological effects at trace levels. Application of AHP in the research conforms to known practices for WQI construction, as evidenced by past studies (Kumar et al., 2024; Sarkar & Majumder, 2021; Horton, 1965; Sutadian et al., 2017; Uddin et al., 2021) and promotes model clarity and contextual applicability for water quality assessment.

3.6 Aggregation function:

Aggregation is the last step of the Water Quality Index (WQI) modeling process. Its purpose is to combine the sub-index values and parameter weightings into an individual numerical index, providing an overall picture of water quality. This process allows for the reduction of complicated, multi-parameter data to a form that can be interpreted by stakeholders, policymakers, and decision-makers at the community level. In this research, following the attribution of weights to every water quality parameter using the Analytic Hierarchy Process (AHP), the performance of seven varied aggregation functions, obtained from existing literature WQI models, was compared. The models used were:

i. Aquatic Toxicity Index
ii. Bascaron Index
iii. Brown Index
iv. Dinius Index
v. Dojlido Index
vi. Scottish Research Development Department (SRDD) Index
vii. West Java Index

All of these models used a distinct mathematical formula to aggregate sub-indices and weighting values. The approaches to aggregation varied from additive (arithmetic) and multiplicative (geometric) methods to minimum operator and non-linear models, differing in their philosophies regarding parameter interaction and impact. The objective of the comparative study was to determine the effect different formulations have on WQI outputs when subjected to the same dataset and weights setup. All the calculations for the aggregation models were carried out in Microsoft Excel 2021 to maintain transparency, reproducibility, and ease of calculation. This comparative framework offers a strong platform for determining the most appropriate aggregation approach in rural water quality situations.

3.7 Entropy-weighted water quality index:

The theory of information entropy was first postulated by (Shannon, 1948) as a basic component of information theory. It was theorized that entropy is a measure of quantified uncertainty or information content of a system. Entropy mathematically has an inverse relation with the probability of occurrence of an event, the lower the probability of entropy, the greater the information entropy. Over the past few years, the theory of entropy has found growing application in different fields of hydrology and water quality evaluation (Adimalla, 2021; Ozkul et al., 2000; Singh et al., 2019) and has proved to be an effective instrument as the Water Quality Index. In order to calculate the Entropy-Based Water Quality Index (EWQI), a set of systematic procedures was followed. The first step is the allocation of an entropy weight to every water quality parameter. To this end, when there are m water samples (i = 1, 2, …, m) and each is analyzed for n quality parameters (j = 1, 2, …, n), an eigenvalue matrix X (Eq. 3.4) is formed based on the data observed.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdot & x_{1n} \\ x_{21} & x_{22} & \cdot & x_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & \cdot & x_{mn} \end{bmatrix} \tag{3.4}$$

This matrix is used as a basis for the calculation of the entropy weights for each parameter. Pre-treatment of data was performed to remove the effect of varying units and scales between water quality parameters. This was done by making use of two normalization functions (Eq. 3.5 & 3.6).

For the efficiency type,

$$y_{ij} = \frac{x_{ij} - (x_{ij})_{min}}{(x_{ij})_{max} - (x_{ij})_{min}} \tag{3.5}$$

For the cost type,

$$y_{ij} = \frac{(x_{ij})_{max} - x_{ij}}{(x_{ij})_{max} - (x_{ij})_{min}} \tag{3.6}$$

The standardized matrix Y (Eq. 3.7) was obtained after undergoing this transformation.

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdot & y_{1n} \\ y_{21} & y_{22} & \cdot & y_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ y_{m1} & y_{m2} & \cdot & y_{mn} \end{bmatrix} \quad (3.7)$$

Next, the proportionate value of the j-th index in the i-th sample was computed using the below (Eq. 3.8).

$$P_{ij} = {y_{ij}}/{\sum_{i=1}^{m} y_{ij}} \quad (3.8)$$

The information entropy is calculated using the formula below (Eq. 3.9)

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} P_{ij} \ln P_{ij} \quad (3.9)$$

Using these entropy values, the entropy-based weight for each parameter was calculated through the corresponding formula (Eq. 3.10)

$$\omega_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \quad (3.10)$$

In the second step of the EWQI calculation, a quality rating (q_j) was assigned to each water quality parameter. This rating was determined using the (Eq. 3.11) that reflects the parameter's concentration relative to the acceptable standards.

$$q_j = ({C_j}/{S_j}) \times 100 \quad (3.11)$$

Where,

C_j = the concentration of each water quality parameter in each water sample in mg/l,

Sj = the limit for drinking water of each parameter in mg/l according to quality standards for drinking water of BIS, CPCB, and WHO.

The EWQI can be calculated in the third step using the following (Eq. 3.12),

$$EWQI = \sum_{j=1}^{n} \omega_j q_j \quad (3.12)$$

The water quality classification scale of EWQI, as suggested by (Jianhua et al., 2011; Singh et al., 2019) is classified into five ranks, ranging from ''excellent'' to ''extremely poor''. The classification ranks are listed in Table 3.4.

Table 3.4 EWQI Scalebar

WQI Range	Water Quality Categories
EWQI<50	Excellent
50-100	Good
100-150	Average
150-200	Poor
EWQI>200	Extremely Poor

3.8 Sensitivity Analysis:

Sensitivity analysis was performed to analyze the relative impact of single water quality parameters on the final Water Quality Index (WQI) scores generated by each model (Li et al., 2013; Rickwood & Carr, 2009; Scheili et al., 2015; Sun et al., 2012). In this present study, the Sensitivity analysis was conducted by omitting particular parameters to determine how they impact the overall index value, hence determining which indicators have the most significant impact on water quality assessment results. This method was used by many researchers, one of the significant studies by (Abtahi et al., 2015). The robustness of the mentioned WQI models was tested in a systematic manner. All sensitivity analysis calculations were performed with Microsoft Excel 2021 to ensure complete transparency and replicability of the results. The analysis was conducted by sequentially deleting one parameter at a time from the input dataset and then recalculating the WQI for each model. The new WQI scores (reduced indices) were subsequently contrasted with the initial full-index values for the same model in order to evaluate the level of variation induced by the exclusion of the parameter. The scale of deviation between the initial and reduced indices is a proxy for that parameter's relative sensitivity in every WQI model. Sensitivity analysis is crucial in assisting in maintaining the robustness of WQI models by determining key parameters that have considerable influence on water quality assessment in the rural setting of Indore villages.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Physicochemical and Heavy Metal Characterisation of Water Samples:

36 water samples were collected from five rural villages of Indore district—Memdi, Simrol, Gokanya, Harsola, and Borkhedi, and analyzed to assess the water quality based on a comprehensive set of physicochemical and heavy metal parameters. The results are the basis for the calculation of the Water Quality Index (WQI) and aid in unveiling site-specific patterns of contamination. Parameters that were analyzed include a total of 24 critical physicochemical indicators, heavy metals, and ionic components.

4.1.1 Borkhedi:

The pH levels at all sites fall within the slightly alkaline to neutral range (7.09 to 8.03) and indicate no short-term threat of acidification, as shown in Table 4.1. Turbidity is highly variable, with very high readings at B1 (6.99 NTU), suggesting the possibility of particulate contamination, while sites such as B3 and B5 indicate little turbidity, perhaps hinting at greater sedimentation or reduced anthropogenic disturbance. Free chlorine is largely zero, with some slight readings at B2, B4, B5, and B6. Alkalinity varies extensively in space from 270.33 mg/l (B2) to a high of 611.67 mg/l (B5), which may be due to variations in carbonate buffering capacity and the geology below. As shown in Figure 4.1 Hardness varies correspondingly from 244.33 to 560.00 mg/l, classifying the water as hard to very hard, likely the result of limestone or gypsum-bearing strata. Electrical conductivity (EC) is also varying, with the higher values showing at B3, B5, B6, and B8 (>1000 µS/cm), pointing towards higher ionic load. BOD_5 and COD levels indicate low to moderate organic contamination, with some peak values (e.g., B3 BOD: 24.09 mg/l), pointing towards localized inflow of biodegradable waste. Chloride levels are below critical levels but exhibit fluctuation, possibly due to discharge from households or natural mineralization. Nitrate levels reach a peak at S6 (11.53 mg/l). Notably, fluoride levels are generally in safe ranges (0.27–1.00 mg/l) except at B4, which registers a high reading of 1.50 mg/l, far exceeding the permissible limit, threatening to cause long-term dental or skeletal fluorosis if ingested regularly without treatment. Calcium and magnesium contents show trends like that of total hardness. High variability between sites indicates the influence of natural and anthropogenic processes, and targeted interventions are required, particularly in high-risk sites, to protect drinking water quality and provide for sustainable resource use in rural Borkhedi.

Table 4. 1 Physicochemical and Heavy Metal Profile of Water Samples from Borkhedi Village (B1–B8)

Parameters Tested[a]	B1	B2	B3	B4	B5	B6	B7	B8
pH	7.97±0.01	7.26±0.00	7.36±0.00	8.03±0.00	7.39±0.01	7.66±0.01	7.41±0.00	7.09±0.00
Turbidity (NTU)	6.99±0.10	2.00±0.00	0.75±0.13	2.27±0.29	0.45±0.05	1.07±0.06	2.27±0.06	1.20±0.00
Free Chlorine (mg/L)	0.003±0.01	0.02±0.01	N.D	0.01±0.01	0.04±0.03	0.15±0.00	N.D	N.D
Alkalinity (mg/L)	289.00±1.00	270.33±1.53	413.67±1.53	350.33±0.58	611.67±0.58	350.67±1.15	404.67±0.58	371.00±1.00
Hardness (mg/L)	255.00±1.00	244.33±1.15	459.00±1.00	300.33±0.58	479.67±0.58	360.00±0.00	459.67±0.58	560.00±0.00
DO (mg/L)	5.33±0.12	5.50±0.00	6.17±0.12	5.10±0.10	5.10±0.00	5.87±0.06	5.50±0.00	4.40±0.00
BOD_5 (mg/L)	6.17±0.06	14.29±0.08	24.09±0.04	12.38±0.01	4.55±0.01	6.52±0.00	6.52±0.01	16.32±0.02
COD (mg/L)	10.55±0.09	31.96±0.06	74.66±0.01	31.96±0.06	10.66±0.01	53.31±0.02	159.63±0.55	74.65±0.02
TSS (mg/L)	299.67±1.53	151.00±1.00	99.33±1.15	145.00±1.00	99.00±1.00	120.33±1.53	250.00±0.00	181.33±0.58
VSS (mg/L)	179.33±1.15	81.33±0.58	65.67±1.15	69.33±0.58	45.00±0.00	54.67±0.58	175.33±0.00	85.00±0.00
Mn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Zn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Fe (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Ni (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Cd (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Na (mg/L)	1.67±1.15	106.67±5.69	76.67±5.86	78.00±0.00	66.00±1.00	67.67±2.52	72.67±2.89	63.00±0.00
K (mg/L)	26.00±0.00	26.00±0.00	26.33±0.58	3.67±0.58	1.67±1.15	2.80±0.00	2.00±0.00	2.63±0.06
Ca (mg/L)	50.00±0.00	66.00±3.46	63.67±4.04	56.33±0.58	99.67±4.73	72.33±3.21	62.00±2.65	58.67±2.52
Cr (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Pb (mg/l)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
EC (μS/cm)	631.23±0.59	912.27±0.31	1176.67±0.58	918.47±0.31	1115.47±0.50	1005.80±0.72	951.40±0.40	1356.93±0.90
F (mg/L)	0.90±0.00	1.00±0.00	0.40±0.00	1.50±0.00	0.27±0.06	0.30±0.00	0.53±0.06	0.27±0.06
Cl- (mg/L)	93.49±0.53	177.61±0.58	195.60±0.59	161.46±0.52	181.61±0.58	161.91±0.08	67.98±0.00	237.71±0.21
NO3- (mg/L)	3.03±0.06	8.53±0.12	6.57±0.06	5.53±0.15	7.63±0.06	11.53±0.06	10.60±0.10	4.07±0.12

[a]Mean ± standard deviation from triplicates, N.D = Not detectable

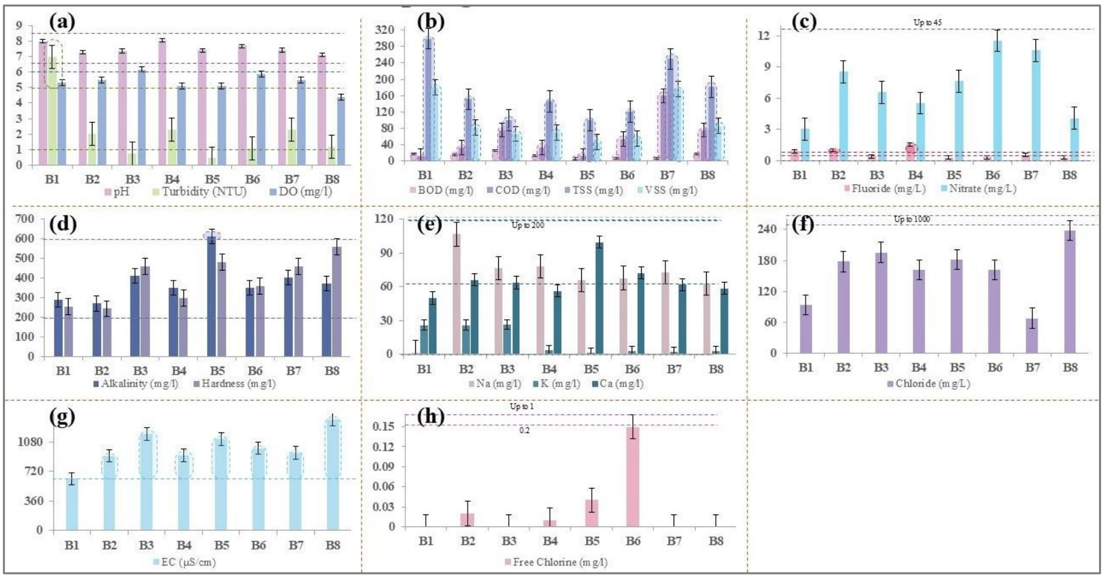

Figure 4. 1 Comparative analysis of key parameters across 8 locations in Borkhedi: (a) pH, Turbidity & DO, (b) BOD, COD, TSS & VSS, (c) Fluoride & Nitrate, (d) Alkalinity & Hardness, (e) Na, K & Ca, (f) Chloride, (g) EC, (h) Free Chlorine

4.1.2 Gokanya:

As shown in Table 4.2, the physicochemical parameters of water quality of Gokanya village at six sampling locations (G1 to G6), the results indicate considerable spatial variability of important physicochemical parameters. pH ranged from 7.09 to 8.18, largely within the acceptable range, signifying slightly alkaline to near-neutral water. Yet turbidity levels were significantly higher at G5 (13.00 NTU), above BIS norms (1 NTU in drinking water), indicating sediment or organic contamination. Free chlorine was missing from all samples except in G6 (0.07 mg/L), meaning poor disinfection, which could be a cause for concern in microbial safety. Alkalinity ranged from 75.33 to 161 mg/L, and hardness showed a dramatic increase at G5 (769 mg/L), indicating possible requirements for water softening. As shown in the Figure 4.2, DO levels were quite moderate (4.00–6.07 mg/L), whereas BOD_5 was at its peak at G3 (7.84 mg/L) and G2 (7.16 mg/L), reflecting high biodegradable organic load, likely from domestic sewage. COD levels were also maximal at G5 & G6, reinforcing the above deduction. TSS and VSS were also at their peaks at G5 (448.67 and 234.67 mg/L, respectively), validating the suspended organic matter. Nitrate levels, especially at G5 (19.47 mg/L), suggest risks of agricultural runoff or fecal contamination. EC ranged from 323.33 to 628.90 µS/cm, with high values suggesting mineral content in water. The fluoride levels were within permissible limits in some locations, though G3 (2.6 mg/L) and G4 (2.1 mg/L) were above

Table 4. 2 Physicochemical and Heavy Metal Profile of Water Samples from Gokanya Village (G1-G6)

Parameters Tested[a]	G1	G2	G3	G4	G5	G6
pH	8.09±0.00	8.18±0.01	7.81±0.01	7.26±0.00	7.09±0.00	8.12±0.01
Turbidity (NTU)	2.60±0.10	0.98±0.03	0.53±0.10	0.57±0.03	13.00±0.00	2.37±0.06
Free Chlorine (mg/L)	N.D	N.D	N.D	N.D	N.D	0.07±0.06
Alkalinity (mg/L)	114.67±0.58	75.33±0.58	80.00±0.00	90.33±0.58	161.00±1.00	120.67±0.58
Hardness (mg/L)	260.00±0.00	249.33±0.58	139.33±1.15	210.00±0.00	769.00±1.00	189.67±0.58
DO (mg/L)	5.87±0.06	4.60±0.00	4.00±0.00	5.30±0.00	6.07±0.06	4.53±0.06
BOD_5 (mg/L)	1.30±0.01	7.16±0.01	7.84±0.02	2.61±0.01	3.90±0.01	3.25±0.01
COD (mg/L)	10.55±0.09	223.50±0.50	202.63±0.04	160.00±0.11	244.93±0.80	288.00±1.00
TSS (mg/L)	198.33±1.53	74.67±0.58	50.33±0.58	44.67±0.58	448.67±1.53	175.00±0.00
VSS (mg/L)	119.33±1.15	39.00±1.00	35.00±0.00	24.67±0.58	234.67±1.53	84.67±0.58
Mn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Zn (mg/L)	N.D	N.D	N.D	1.425±0.001	N.D	N.D
Fe (mg/L)	N.D	N.D	N.D	N.D	0.358±0.001	N.D
Ni (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Cd (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Na (mg/L)	73.00±0.00	65.67±1.76	62.50±0.50	147.33±3.06	22.67±2.02	16.83±2.02
K (mg/L)	0.67±0.29	0.70±0.17	0.33±0.29	1.17±0.29	0.17±0.29	2.33±0.76
Ca (mg/L)	1.50±0.50	0.73±0.21	6.17±1.26	1.00±0.00	8.67±1.26	0.50±0.00
Cr (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Pb (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
EC (μS/cm)	628.90±0.10	570.37±0.15	600.80±0.26	499.53±0.15	323.33±1.53	318.10±0.10
F (mg/L)	0.90±0.00	1.10±0.00	2.60±0.00	2.10±0.00	0.70±0.00	0.33±0.06
Cl- (mg/L)	111.41±0.73	85.96±0.01	139.62±0.32	231.93±0.00	215.91±0.03	81.95±0.03
NO3- (mg/L)	5.33±0.06	7.57±0.06	7.67±0.06	6.43±0.06	19.47±0.31	1.50±0.00

[a]Mean ± standard deviation from triplicates, N.D = Not detectable

the WHO permissible limit of 1.5 mg/L, with implications for health in the form of fluorosis. Chloride levels were high at G4 and G5 (>200 mg/L) and may be a result of anthropogenic discharge. Heavy metal elements such as Manganese, Nickel, Cadmium, Chromium, and Lead were mostly not detected. High Na at G4 (147.33 mg/L) indicates potential salinity problems. These results necessitate specific water treatment measures at points such as G3, G4, and G5, where most of the parameters exceed safety limits. Overall, while some locations exhibit acceptable water quality, others indicate anthropogenic pollution, necessitating localized management and periodic monitoring.

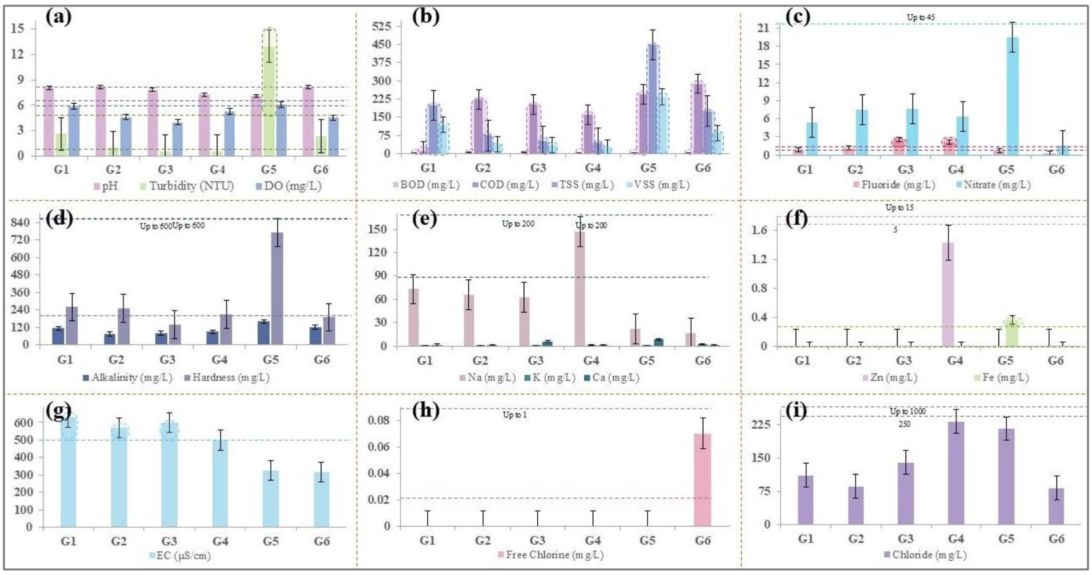

Figure 4. 2 Comparative analysis of key parameters across 6 locations in Gokanya: (a) pH, Turbidity & DO, (b) BOD, COD, TSS & VSS, (c) Fluoride & Nitrate, (d) Alkalinity & Hardness, (e) Na, K & Ca, (f) Zn & Fe, (g) EC, (h) Free Chlorine (i) Chloride

4.1.3 Harsola:

The quality of water in Harsola village, as analysed from eight samples (H1 to H8), indicates mixed properties in the area, as shown in Table 4.3. The pH ranges between 6.96 and 8.01, representing slightly alkaline to moderately alkaline conditions, still within safe drinking water limits. Turbidity levels are low (0.3–1 NTU) at most sites, indicating clean water, except for H4 and H5, where turbidity peaks at 25.67 and 28 NTU, respectively, indicating potential particulate contamination, perhaps due to soil runoff or unlined source storage. Free chlorine, a disinfection indicator, is practically zero in most samples (0.00–0.04 mg/L), with the only exceptions being H4 and H5 (0.34 and 0.28 mg/L), which indicate random or low-level chlorination practices in the village. Alkalinity, a measure of the water's buffering capacity, varies from 369 mg/L (H4) to 1234.33 mg/L (H6), with several samples (H2, H3, H6, H7) going beyond desirable limits in standards (>600 mg/L) and posing the risks of an

Table 4. 3 Physicochemical and Heavy Metal Profile of Water Samples from Harsola Village (H1-H8)

Parameters Tested[a]	H1	H2	H3	H4	H5	H6	H7	H8
pH	7.01±0.00	7.76±0.01	7.50±0.01	8.01±0.01	7.97±0.06	7.26±0.04	6.96±0.06	7.09±0.00
Turbidity (NTU)	0.30±0.01	1.00±0.00	0.35±0.01	25.67±0.58	28.00±0.00	0.35±0.00	0.68±0.03	0.87±0.03
Free Chlorine (mg/L)	N.D	0.03±0.00	N.D	0.34±0.00	0.28±0.01	0.02±0.00	N.D	0.04±0.00
Alkalinity (mg/L)	449.00±0.00	909.33±0.58	790.00±0.00	369.00±1.00	395.33±0.58	1234.33±0.58	1109.33±0.58	480.00±0.00
Hardness (mg/L)	610.00±0.00	228.67±1.15	271.00±1.00	149.33±1.15	144.33±1.15	461.00±1.00	439.67±0.58	260.67±1.15
DO (mg/L)	5.13±0.06	5.87±0.06	6.10±0.00	5.43±0.12	5.67±0.12	5.00±0.00	4.50±0.00	5.17±0.06
BOD_5 (mg/L)	11.07±0.01	7.27±0.12	6.51±0.02	5.22±0.01	6.17±0.15	10.43±0.00	15.58±0.11	8.13±0.12
COD (mg/L)	74.66±0.01	10.66±0.01	21.33±0.00	53.28±0.07	10.66±0.01	95.33±0.58	53.32±0.01	10.66±0.01
TSS (mg/L)	50.00±0.00	151.00±1.00	74.67±0.58	500.00±0.00	545.00±5.00	85.00±0.00	100.00±0.00	75.33±0.58
VSS (mg/L)	35.00±0.00	85.33±0.58	30.00±0.00	294.67±0.58	310.00±0.00	34.67±0.58	69.67±0.00	40.00±0.00
Mn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Zn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Fe (mg/L)	N.D	N.D	N.D	N.D	0.427±0.001	0.406±0.001	N.D	N.D
Ni (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Cd (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Na (mg/L)	98.67±1.15	124.00±3.46	118.67±3.51	15.00±0.00	15.33±0.58	75.33±1.15	92.33±1.53	72.67±2.52
K (mg/L)	20.67±1.15	10.00±1.73	29.33±1.53	16.00±1.73	18.67±0.58	59.00±0.00	42.00±1.73	40.33±0.58
Ca (mg/L)	101.67±2.89	90.67±2.31	60.00±2.65	7.33±0.58	6.67±0.58	85.00±0.00	107.33±0.58	35.00±0.00
Cr (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Pb (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
EC (μS/cm)	1718.00±1.00	1084.33±1.15	1180.33±1.53	243.53±0.06	242.90±0.10	1314.67±0.58	1176.33±1.53	787.60±0.20
F (mg/L)	1.37±0.06	0.97±0.06	1.50±0.00	2.57±0.06	0.20±0.00	0.70±0.00	0.60±0.00	0.80±0.00
Cl- (mg/L)	219.44±0.53	193.80±0.16	297.78±0.23	59.81±0.22	47.82±0.19	265.61±0.54	197.65±0.27	91.62±0.31
NO3- (mg/L)	2.33±0.06	9.47±0.72	10.10±0.69	0.67±0.12	0.50±0.00	7.53±0.15	3.50±0.36	4.10±0.10

[a]Mean ± standard deviation from triplicates, N.D = Not detectable

overabundance of carbonate and bicarbonate ions that may affect taste and plumbing. In the same manner, total hardness, which is an analysis of calcium and magnesium salts, ranges extensively from 144.33 mg/L (H5) to 610 mg/L (H1), while H1, H3, H6, and H7 are categorized under very hard water (>300 mg/L), which shows possible scaling concerns and the requirement for softening in household application. The dramatic difference between low-turbidity and highly alkaline/hard profiles in certain samples indicates various sources or aquifers being exploited, each with unique geochemical reactions.

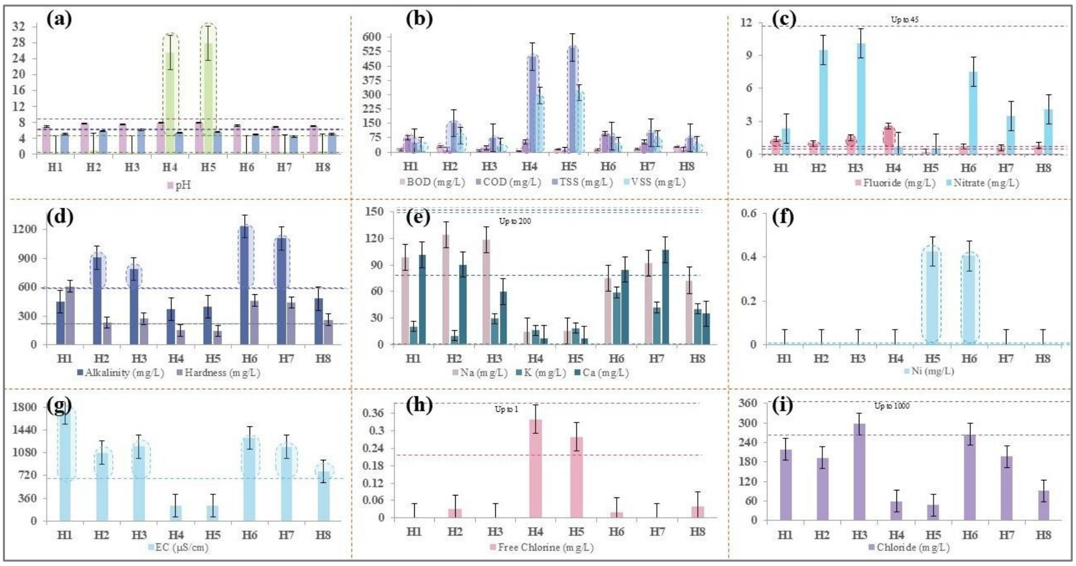

Figure 4. 3 Comparative analysis of key parameters across 8 locations in Harsola: (a) pH, Turbidity & DO, (b) BOD, COD, TSS & VSS, (c) Fluoride & Nitrate, (d) Alkalinity & Hardness, (e) Na, K & Ca, (f) Ni, (g) EC, (h) Free Chlorine (i) Chloride

4.1.4 Memdi:

According to the water quality data analysed from Memdi village at eight monitoring stations (M1–M8), various notable trends were observed as shown in Table 4.4. The pH ranges between 6.95 and 8.48, showing predominantly neutral to mildly alkaline conditions, with M5 and M8 being on the higher side, possibly because of alkaline runoff or the presence of carbonates. Turbidity was very variable, with M6 and M7 having notably high values (~18–19 NTU), which suggests intense particulate content, likely from proximal anthropogenic activity or surface erosion. Free chlorine was predominantly non-detected, with only trace levels detected in M4, M7, and M8, suggesting poor or spasmodic disinfection. Alkalinity concentrations were highly variable, with M3, M6, and M7 having high values, indicative of buffering capacity against pH shift, possibly due to bicarbonate-rich geology. Hardness was most elevated at M3, M6, and M7, indicative of possible health effects and scaling, potentially due to the presence of calcium and magnesium salts from geological sources or wastewater seepage. DO values, which are most essential for aquatic health, were below the optimum level at most of the sites, especially at M7 (2.57 mg/L), indicating possible organic pollution. BOD_5 and COD values were extremely high, especially at M7 (BOD: 110.17 mg/L, COD: 201.10 mg/L), which validated high organic load, possibly due to unhindered domestic discharges. TSS and VSS data also corroborate this, with M7 once more exhibiting extreme values (TSS: 500.67 mg/L, VSS: 401.50 mg/L), reflecting high levels of suspended and organic solids. These higher values reflect compromised water quality and worse conditions in some areas.

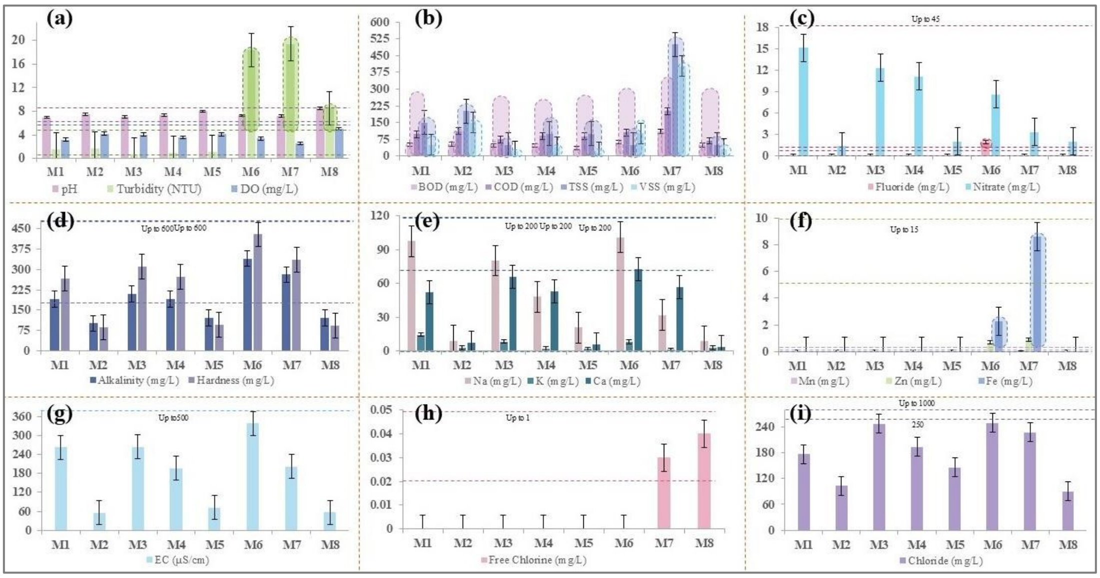

Figure 4. 4 Comparative analysis of key parameters across 8 locations in Harsola: (a) pH, Turbidity & DO, (b) BOD, COD, TSS & VSS, (c) Fluoride & Nitrate, (d) Alkalinity & Hardness, (e) Na, K & Ca, (f) Mn, Zn & Fe, (g) EC, (h) Free Chlorine (i) Chloride

4.1.5 Simrol:

The water quality profile of Simrol village water quality through tested samples (S1–S6) presents a complex array of variables that depict natural and human-induced factors as shown in Table 4.5. The pH range in all samples is within the acceptable limit for potable water (6.5–8.5). Turbidity levels have great variability, with S1 having the highest at 9.10 NTU, reflecting suspended particulate matter, probably due to surface runoff or unlined channels, and S4 and S5 having much clearer water. Free chlorine, an indicator for disinfection, does not exist in the majority of samples except S1, S2, S4, and S6, reflecting irregular chlorination or chlorination breakdown in warm temperatures. Alkalinity is between 60 and 110 mg/L, indicating moderate buffering capacity, with S1 being the highest, perhaps due to leaching of bicarbonate from local soil. Hardness is variable, with S1 showing the highest (163.67 mg/L), indicating the presence of calcium and magnesium, which may be geological deposits.

Table 4. 4 Physicochemical and Heavy Metal Profile of Water Samples from Memdi Village (M1-M8)

Parameters Tested[a]	M1	M2	M3	M4	M5	M6	M7	M8
pH	6.95±0.04	7.48±0.01	7.06±0.01	7.32±0.01	8.01±0.01	7.29±0.01	7.17±0.01	8.48±0.01
Turbidity (NTU)	1.56 ± 0.05	1.68 ± 0.04	0.63 ± 0.02	0.90 ± 0.08	1.16 ± 0.04	18.33 ± 0.05	19.43 ± 0. 04	8.51 ± 0. 03
Free Chlorine (mg/L)	N.D	N.D	N.D	0.02 ± 0.01	N.D	N.D	0.03 ± 0.02	0.04 ± 0.01
Alkalinity (mg/L)	190.33±0.58	100.33±0.58	210.33±0.58	190.67±1.15	120.67±1.15	340.67±0.58	281.00±1.00	121.33±1.15
Hardness (mg/L)	265.43±0.15	86.30±0.05	310.38±0.45	271.58±0.30	96.50±0.02	429.32±0.74	334.68±0.20	93.33±0.16
DO (mg/L)	3.17±0.21	4.20±0.10	4.07±0.12	3.57±0.06	4.13±0.06	3.40±0.10	2.57±0.06	5.03±0.06
BOD_5 (mg/L)	50.03±0.06	52.87±1.33	48.17±0.15	46.07±0.06	35.10±0.10	62.10±0.10	110.17±0.15	49.23±0.25
COD (mg/L)	98.13±0.12	111.22±0.19	74.17±0.15	90.40±0.53	88.20±0.26	105.37±0.40	201.10±1.01	68.23±0.32
TSS (mg/L)	150.33±0.58	200.50±0.50	50.67±0.58	100.83±0.29	50.00±0.00	150.83±0.76	500.67±1.15	50.83±0.29
VSS (mg/L)	50.33±0.58	150.33±0.58	20.51±0.50	40.33±0.58	15.29±0.28	101.00±1.00	401.50±1.80	30.50±0.50
Mn (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	0.054±0.002	N.D
Zn (mg/L)	N.D	N.D	N.D	N.D	N.D	0.69±0.03	0.90±0.01	N.D
Fe (mg/L)	N.D	N.D	N.D	N.D	N.D	2.254±0.003	8.608±0.004	N.D
Ni (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Cd (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Na (mg/L)	97.67±0.29	9.00±0	80.33±3.69	48±2.29	20.83±1.76	101.17±9.41	31.83±4.25	8.50±1.50
K (mg/L)	14.50±0	2.63±0.06	8.33±0.49	2.00±0	1.63±0.06	7.97±0.15	0.87±0.15	2.77±0.32
Ca (mg/L)	52.50±0.87	7.00±0.87	65.83±2.52	52.67±2.52	5.83±0.76	72.67±3.55	56.67±1.76	3.33±0.32
Cr (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
Pb (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
EC (µS/cm)	261.73±0.21	56.07±1.10	263.26±0.02	196.05±0.02	72.38±0.03	337.23±0.07	201.26±0.03	57.45±0.04
F (mg/L)	N.D	N.D	N.D	N.D	N.D	1.90±0.00	N.D	N.D
Cl- (mg/L)	177.46±0.50	103.41±0.79	247.92±0.00	193.62±0.55	145.95±0.00	249.71±0.21	227.55±0.50	89.96±0.02
NO3- (mg/L)	15.10±0.17	1.33±0.06	12.33±0.06	11.13±0.40	2.03±0.06	8.60±0.10	3.33±0.06	2.00±0.00

DO levels are found to be mostly adequate (more than 5 mg/L) in all areas except S3 and S5, where DO decreases to 3.2 and 3.7 mg/L, respectively, due to high organic load and microbial oxygen uptake. Accordingly, BOD_5 and COD levels at S1 are distressingly high (82.17 mg/L and 180.10 mg/L, respectively), suggesting ample biodegradable organic content, presumably from residential wastes. While S3–S6 possess moderate BOD_5 & COD values, these are still higher than normal limits, which suggests continuous pollution. Total suspended solids and volatile suspended solids are also high in most samples, particularly S2, S3, and S5, which might further reduce DO values through microbial processes. The high and persistent BOD_5, COD, and suspended solids in most samples suggest impaired water quality that might be ecologically and humanly hazardous.

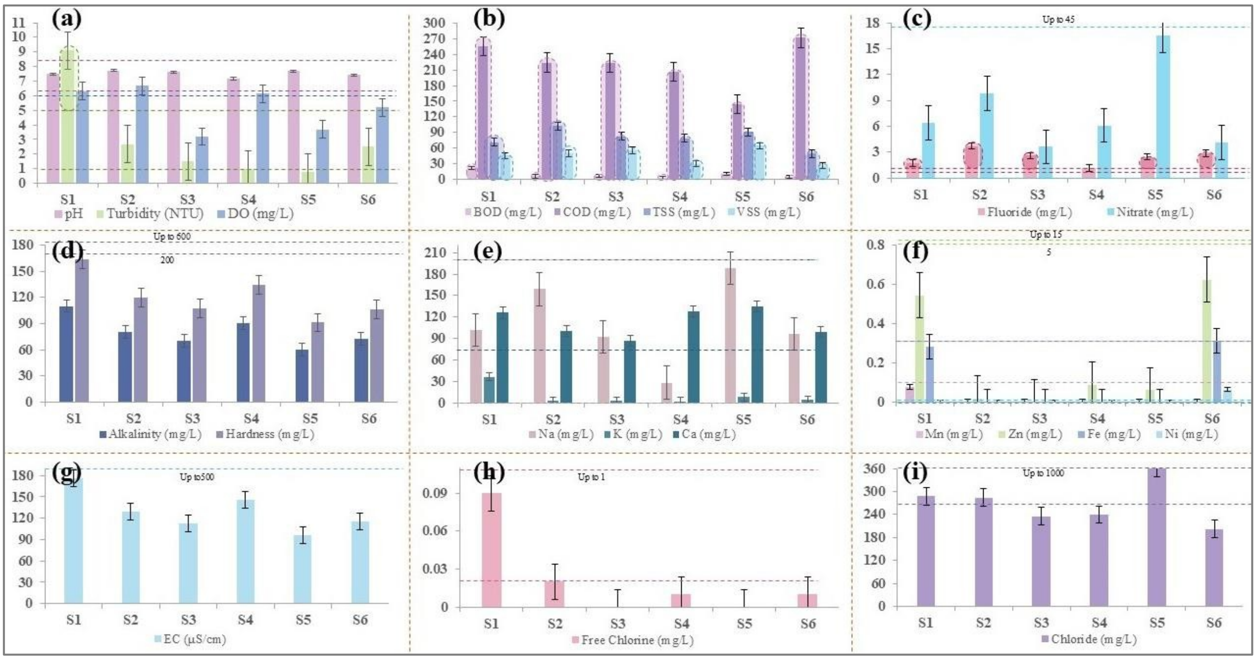

Figure 4. 5 Comparative analysis of key parameters across 8 locations in Harsola: (a) pH, Turbidity & DO, (b) BOD, COD, TSS & VSS, (c) Fluoride & Nitrate, (d) Alkalinity & Hardness, (e) Na, K & Ca, (f) Mn, Zn, Fe & Fe, (g) EC, (h) Free Chlorine (i) Chloride

4.2 Sub-indices of water quality parameters:

The sub-index scores were calculated on a 0–100 scale in which a value of 100 represented outstanding water quality for a particular parameter, and decreasing values correspond to increasing quality and augmented pollution loads. The sub-index scores were the basic inputs in all subsequent WQI model aggregations, making it possible for final score computation model-wise in all index frameworks. Table 4.6 below shows the sub-index values of all water quality parameters for different villages.

Table 4. 5 Physicochemical and Heavy Metal Profile of Water Samples from Simrol Village (S1-S6)

Parameters Tested[a]	S1	S2	S3	S4	S5	S6
pH	7.48±0.01	7.73±0	7.62±0.01	7.18±0.01	7.68±0	7.41±0.01
Turbidity (NTU)	9.10 ± 0.01	2.68 ± 0.03	1.51 ± 0.01	0.96 ± 0.01	0.77 ± 0.02	2.52 ± 0.02
Free Chlorine (mg/L)	0.09 ± 0	0.02 ± 0.01	N.D	0.01 ± 0.01	N.D	0.01 ± 0
Alkalinity (mg/L)	110.33±0.58	80.67±1.15	70.67±1.15	91.00±1.73	60.33±0.58	72.33±2.52
Hardness (mg/L)	163.67±1.53	120.01±1.52	107.22±1.03	134.70±2.38	91.33±1.04	106.30±1.97
DO (mg/L)	6.33±0.06	6.67±0.06	3.20±0.10	6.13±0.06	3.70±0	5.20±0.10
BOD_5 (mg/L)	82.17±0.15	56.13±0.15	47.33±0.31	44.23±0.25	59.10±0.10	60.27±0.25
COD (mg/L)	180.10±0.10	98.10±0.10	72.10±0.17	86.17±0.15	91.17±0.15	101.33±1.53
TSS (mg/L)	71.67±1.53	102.33±2.52	83.33±1.53	79.33±1.15	91.33±1.15	50.00±0
VSS (mg/L)	46.00±1.00	50.67±1.15	56.33±1.53	30.33±1.53	65.00±2.00	26.67±1.15
Mn (mg/L)	0.078±0.002	N.D	N.D	N.D	N.D	N.D
Zn (mg/L)	0.544±0.004	0.018±0.001	N.D	0.087±0	0.061±0.002	0.624±0.005
Fe (mg/L)	0.282±0.001	0	N.D	N.D	N.D	0.314±0.001
Ni (mg/L)	N.D	N.D	N.D	N.D	N.D	0.062±0.002
Cd (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Na (mg/L)	101.80±1.51	159.00±6.09	92.40±1.20	28.80±3.65	188.07±8.02	96.50±0.70
K (mg/L)	36.57±0.38	3.57±0.15	3.60±0	2.40±0	8.40±0	4.47±0.31
Ca (mg/L)	126.00±1.04	100.60±2.42	87.00±2.16	128±0.35	134.80±3.08	99.47±0.70
Cr (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
Pb (mg/L)	N.D	N.D	N.D	N.D	N.D	N.D
EC (µS/cm)	176.63±0.12	129.01±0.12	113.08±0.01	145.68±0.07	96.29±0.27	115.65±0.09
F (mg/L)	1.70±0.00	3.70±0.00	2.60±0.00	1.17±0.06	2.43±0.15	2.87±0.06
Cl- (mg/L)	287.91±0.00	283.52±0.41	235.61±0.55	239.93±0.00	361.54±0.36	202.47±0.53
NO3- (mg/L)	6.37±0.64	9.83±0.06	3.63±0.06	6.10±0.17	16.50±0.26	4.13±0.06

Table 4. 6 Sub-Indices value of Water Quality parameters in Borkhedi

SI for B1	SI for B2	SI for B3	SI for B4	SI for B5	SI for B6	SI for B7	SI for B8
100.00	38.00	100.00	76.50	44.50	58.00	45.50	29.50
0.00	50.00	81.25	43.25	88.75	73.25	43.25	70.00
100.00	97.50	100.00	98.75	95.00	81.25	100.00	100.00
77.75	82.42	46.58	62.42	0.00	62.33	48.83	57.25
86.25	88.92	35.25	74.92	30.08	60.00	35.08	10.00
88.83	91.67	100.00	85.00	85.00	97.83	91.67	73.33
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
99.17	46.67	61.67	61.00	67.00	66.17	63.67	68.50
87.00	87.00	86.84	98.17	99.17	98.60	99.00	98.69
60.00	47.20	49.06	54.94	20.26	42.14	50.40	53.06
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	0.00	100.00	46.00	100.00	100.00	100.00
87.53	76.32	73.92	78.47	75.79	78.41	90.94	68.31
93.27	81.04	85.40	87.71	83.04	74.38	76.44	90.96

Table 4. 7 Sub-Indices value of Water Quality parameters in Gokanya

SI for G1	SI for G2	SI for G3	SI for G4	SI for G5	SI for G6
100.00	100.00	100.00	38.00	29.50	100.00
35.00	75.50	86.75	85.75	0.00	40.75
71.33	81.17	80.00	77.42	59.75	69.83
121.33	131.17	130.00	127.42	109.75	119.83
85.00	87.67	115.17	97.50	0.00	102.58
97.83	76.67	66.67	88.33	100.00	75.50
35.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	85.75	100.00	100.00
100.00	100.00	100.00	100.00	0.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00
63.50	67.17	68.75	26.34	88.67	91.59
99.67	99.65	99.84	99.42	99.92	98.84
98.80	99.42	95.06	99.20	93.06	99.60
0.00	0.00	0.00	0.09	35.33	36.38
100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00
100.00	80.00	0.00	0.00	100.00	100.00
85.15	88.54	81.38	69.08	71.21	89.07
88.16	83.18	82.96	85.71	56.73	96.67

Table 4. 8 Sub-Indices value of Water Quality parameters in Memdi

SI for M1	SI for M2	SI for M3	SI for M4	SI for M5	SI for M6	SI for M7	SI for M8
22.50	49.00	28.00	41.00	75.50	39.50	33.50	99.00
61.00	58.00	84.25	77.50	71.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	96.25	95.00
52.42	74.92	47.42	52.33	69.83	14.83	29.75	69.67
83.64	100.00	72.41	82.11	100.00	42.67	66.33	100.00
52.83	70.00	67.83	59.50	68.83	56.67	42.83	83.83
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	73.00	100.00
100.00	100.00	100.00	100.00	100.00	93.10	91.00	100.00
100.00	100.00	100.00	100.00	100.00	0.00	0.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
51.17	95.50	59.84	76.00	89.59	49.42	84.09	95.75
92.75	98.69	95.84	99.00	99.19	96.02	99.57	98.62
58.00	94.40	47.34	57.86	95.34	41.86	54.66	97.34
47.65	88.79	47.35	60.79	85.52	32.55	59.75	88.51
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	0.00	100.00	100.00
76.34	86.21	66.94	74.18	80.54	66.71	69.66	88.01
66.44	97.04	72.60	75.27	95.49	80.89	92.60	95.56

Table 4. 9 Sub-Indices value of Water Quality parameters in Simrol

SI for S1	SI for S2	SI for S3	SI for S4	SI for S5	SI for S6
49.00	61.50	56.00	34.00	59.00	45.50
0.00	33.00	62.25	76.00	80.75	37.00
88.75	97.50	100.00	98.75	100.00	98.75
72.42	79.83	82.33	77.25	84.92	81.92
59.08	70.00	73.20	66.33	77.17	73.43
100.00	100.00	53.33	100.00	61.67	86.67
0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00
61.00	100.00	100.00	100.00	100.00	100.00
94.56	99.82	100.00	99.13	99.39	93.76
94.00	100.00	100.00	100.00	100.00	0.00
100.00	100.00	100.00	100.00	100.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00
49.10	20.50	53.80	85.60	5.97	51.75
81.72	98.22	98.20	98.80	95.80	97.77
59.20	79.52	90.40	57.60	52.16	80.42
64.67	74.20	77.38	70.86	80.74	76.87
100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00
61.61	62.20	68.59	68.01	51.79	73.00
85.84	78.16	91.93	86.44	63.33	90.82

Table 4. 10 Sub-Indices value of Water Quality parameters in Harsola

SI for H1	SI for H2	SI for H3	SI for H4	SI for H5	SI for H6	SI for H7	SI for H8
25.50	63.00	50.00	75.50	73.50	38.00	23.00	29.50
92.50	75.00	91.25	0.00	0.00	91.25	83.00	78.25
100.00	96.25	100.00	57.50	65.00	97.50	100.00	95.00
0.00	0.00	0.00	7.75	1.17	0.00	0.00	0.00
0.00	92.83	82.25	100.00	113.92	34.75	40.08	84.83
85.50	97.83	100.00	90.50	94.50	83.33	75.00	86.17
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	0.00	0.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
50.67	38.00	40.67	92.50	92.34	62.34	53.84	63.67
89.67	95.00	85.34	92.00	90.67	70.50	79.00	79.84
18.66	27.46	52.00	94.14	94.66	32.00	14.14	72.00
0.00	0.00	0.00	51.29	51.42	0.00	0.00	0.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
26.00	100.00	0.00	100.00	0.00	0.00	0.00	0.00
70.74	74.16	60.30	92.03	93.62	64.59	73.65	87.78
94.82	78.96	77.56	98.51	98.89	83.27	92.22	90.89

4.3 Weightage of Parameters:

AHP was used in this study to allocate weights through a structured decision framework that allows for pairwise comparison of parameters in accordance with how important each parameter is to the quality of drinking water. AHP calculations were done with the aid of Microsoft Excel 2021, where a pairwise comparison matrix was created. To ensuring reasonable consistency in judgment, the Consistency Ratio (CR) was determined and found to be 0.0977, well below the acceptable limit of 0.10. This validates that the matrix is consistent and reliable, thereby establishing the validity of the weighting process. As shown in Figure 4.6, Parameters with severe human health hazards like lead (Pb), cadmium (Cd), chromium (Cr), and nitrate (NO_3^-) were weighted more heavily because of their toxicological effects even at trace concentrations. BOD_5, COD, fluoride, iron (Fe), and turbidity, which are moderately weighted parameters, show organic contamination or aesthetic issues.

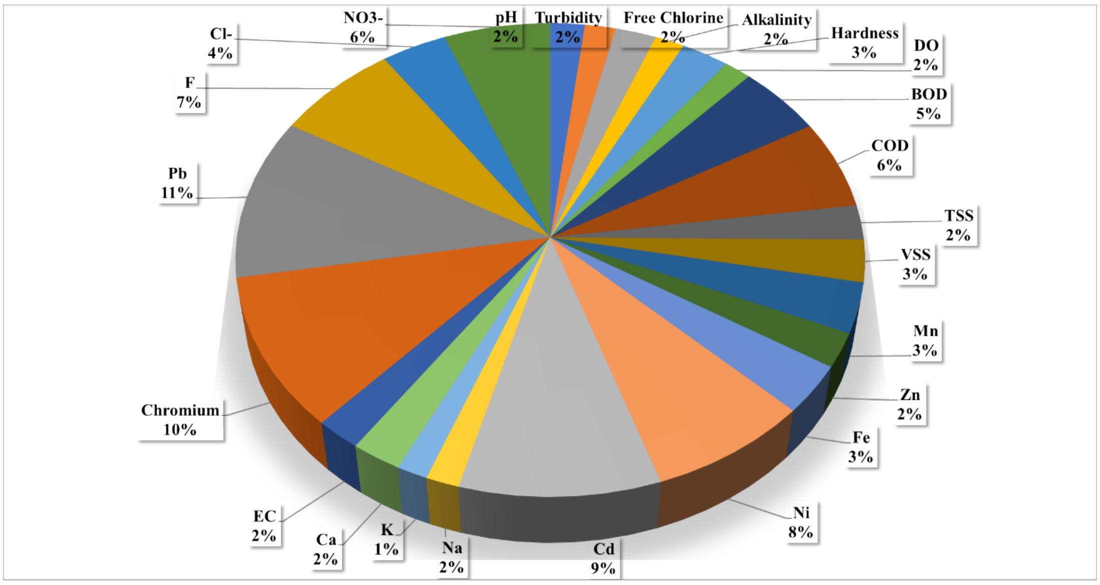

Figure 4. 6 AHP Weightage

Conversely, parameters such as potassium (K), sodium (Na), and free chlorine were assigned lesser weights due to their comparatively lesser health risks and rural site variance in detection. This organised and validated method adds to the scientific and contextual strength of the WQI framework application for rural water quality monitoring in Indore's villages.

4.4 WQI values:

4.4.1 Borkhedi:

The comparative Water Quality Index (WQI) analysis of Borkhedi's eight sampling sites (B1–B8), evaluated using seven established models, Bascaron, Brown, SRDD, Aquatic Toxicity, Dojlido, West Java, and Dinius, reveals marked inter-model variability, shaped by each model's aggregation logic as shown in Figure 4.7. However, the Dojlido index usually records high values: B1, 100; B4, 88.31; and B6, 90.56, putting several sites under "excellent" to "good" categories.

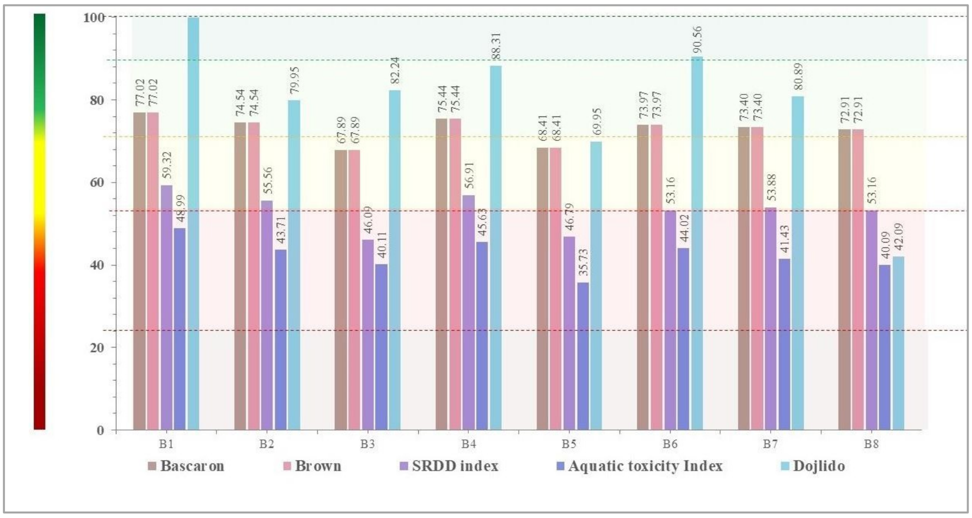

Figure 4. 7 WQI Values of Borkhedi

However, more conservative models, such as SRDD and Aquatic Toxicity Index, record lower values, placing B5, B3, and B8 under the "moderate to poor" category, due to sensitivity toward the parameters of BOD, COD, nitrate, and turbidity. Notably, in both Dinius and West Java indices, WQI values reduce to zero for all samples because of the multiplicative aggregation structure, where the value of a single critical pollutant nullifies the overall index, emphasizing no compromise in any dimension of water quality. These formulations, stringent as they are, emphasize cumulative pollution impact, supporting the requirement for all fundamental quality parameters to be fulfilled.

4.4.2 Memdi:

WQI evaluation of Memdi village at eight sampling locations (M1–M8) indicates model-dependent categorizations, indicating variable levels of contamination and model sensitivity as shown in the Figure 4.8. The highest values throughout the sites are reported by the Dojlido index, which rates M2, M5, and M8 as 94.96, 100, and 100, respectively—"excellent" water quality. But this positive presentation is decidedly different from the more conservative ratings of SRDD and Aquatic Toxicity Index. For example, M6 and M7 rate 25.60 and 33.60 with the Aquatic Toxicity model, which positions them as "poor," most likely because of high BOD_5, COD, or turbidity. Likewise, SRDD ratings for M3 and M6 (44.88 and 51.15) mark moderate to poor water quality, adding to the concern. Bascaron and Brown models all sit at most sites between 60 and 80, providing a balanced reading. Sites M5 and M8, which have the same uniform high score on all the models, seem to have good water quality and could be assisted by well-conserved sources or low anthropogenic pressure. The divergent performance between models, particularly between additive and multiplicative models, supports multi-model verification to avoid spurious classification.

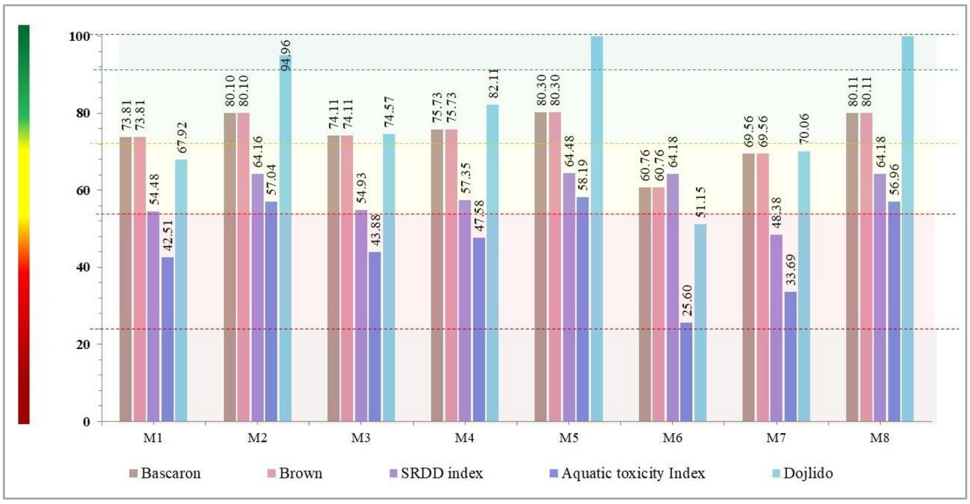

Figure 4. 8 Values of Memdi

4.4.3 Simrol:

The Water Quality Index (WQI) assessment of Simrol village at six locations (S1–S6) indicates significant inter-model variation, exemplifying the significance of aggregation logic in determining ultimate classification. As shown in Figure 4.9, the Dojlido model gives the higher ranks to all locations, with S3 (89.97), S5 (83.69), and S6 (83.92) getting close to the "excellent" category. Conversely, the SRDD and Aquatic Toxicity Index models that focus on environmental risk and health issues rank some of the sites, most notably S1 and S5, as "poor to very poor" with scores as low as 27.86 and 27.94, respectively. These low scores indicate the presence of key pollutants like high BOD_5, low DO, or excess turbidity. S1 stands out as the most impaired site, with Aquatic Toxicity and Dojlido giving the lowest score on all indices (27.86 and 28.55), indicating various parameter exceedances. While S3 and S4 are consistently high on most models, this implies stable groundwater or relatively shielded sources. Most samples fall into the moderate to good category using Brown and Bascaron indices, providing a middle ground between rigorous and liberal extremes. Notably, S5 shows the highest divergence with values between 83.69 (Dojlido) and 27.94 (Aquatic Toxicity), showcasing the significance of model choice in the proper evaluation of water safety. The findings highlight the need for the use of several WQI models together, since depending on one model might underestimate the contamination (as is the case with Dojlido) or even overestimate individual parameter infringements (as in SRDD).

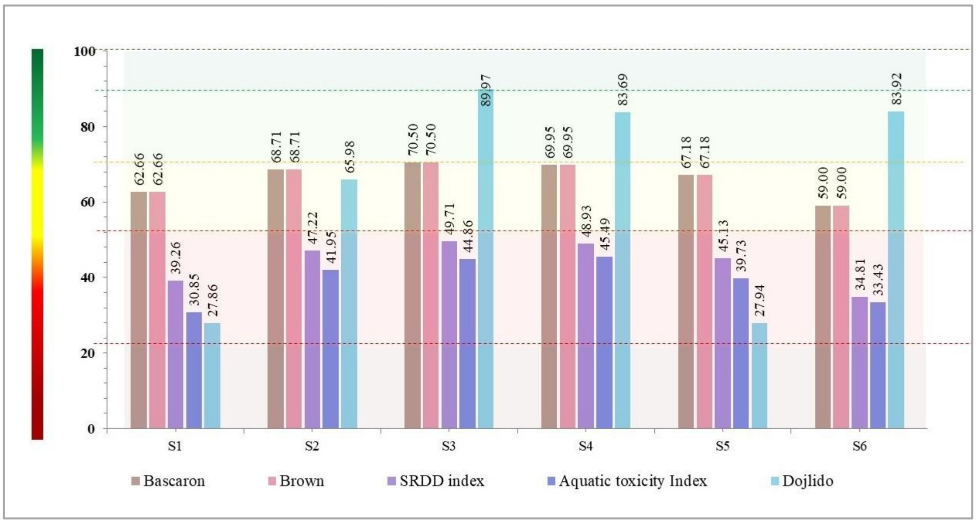

Figure 4. 9 Values of Simrol

4.4.4 Gokanya:

WQI analysis of Gokanya's six sampling points (G1–G6) under several different index models indicates substantial differences in the interpretation of water quality based on the model employed, as shown in Figure 4.10.

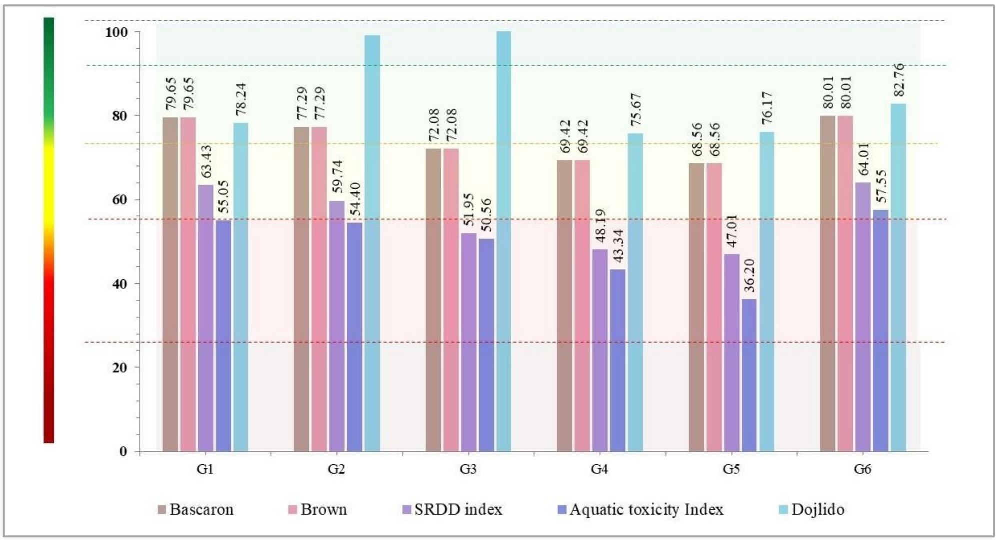

Figure 4. 10 WQI Values of Gokanya

The Dojlido index presents high values for most samples. The Dinius WQI and West Java index values are zero for all samples, emphasizing the models' strict sensitivity towards any extreme exceedance. The SRDD and Aquatic Toxicity indices, with their conservative and health-oriented weighting, place G5 and G4 in the "poor" category (WQI < 50) as signs of likely contamination by organics or turbidity. To be precise, G5 indicates a WQI of 36.20 (SRDD) and 0.46 (Aquatic Toxicity Index)—the most degraded site, possibly due to high BOD_5 or COD. By comparison, G6 performs well uniformly in all models with WQI of 80.01

(Brown), 84.54 (Dojlido), and 64.01 (Aquatic Toxicity), indicating it is the best of all for consumption. Bascaron and Brown models tend to place all samples in the "moderate to good" category, but lack the clear discrimination provided by SRDD and Dojlido. The findings reveal that model choice plays a vital role in the interpretation of the final WQI. Whereas Dojlido could hide local pollution through averaging, multiplicative models such as Dinius and West Java reveal decisive failures.

4.4.5 Harsola:

The eight water sampling points of Harsola (H1–H8) analyzed for water quality index show model-specific water quality classification as per varied aggregation approaches. As shown in Figure 4.11, the Dojlido index, which tends to be higher in values, categorizes H3, H5, and H8 as excellent (WQI > 85), with H5 having 100, indicating none of the parameters were below threshold in this model's computation. In contrast, the SRDD and Aquatic Toxicity Index provide very conservative predictions, with H1, H2, H5, and H7 belonging to the "poor to moderate" category. H1, H5, and H7 are especially health-impacting public health concerns, having scores less than 45 in SRDD and Aquatic Toxicity models, indicating high sensitivity to parameters such as DO, COD, turbidity, and nitrates. H6 and H7 possess Aquatic Toxicity scores of only 27.45 and 30.89, indicating severe degradation and possible chemical or organic pollution. In contrast, H3 and H8 show relatively stable and good-quality water in most models, implying good aquifer conditions or negligible anthropogenic interference. Brown and Bascaron indices are moderate throughout, classifying most sites in the 60–70 WQI range, falling under the "moderate to good" category.

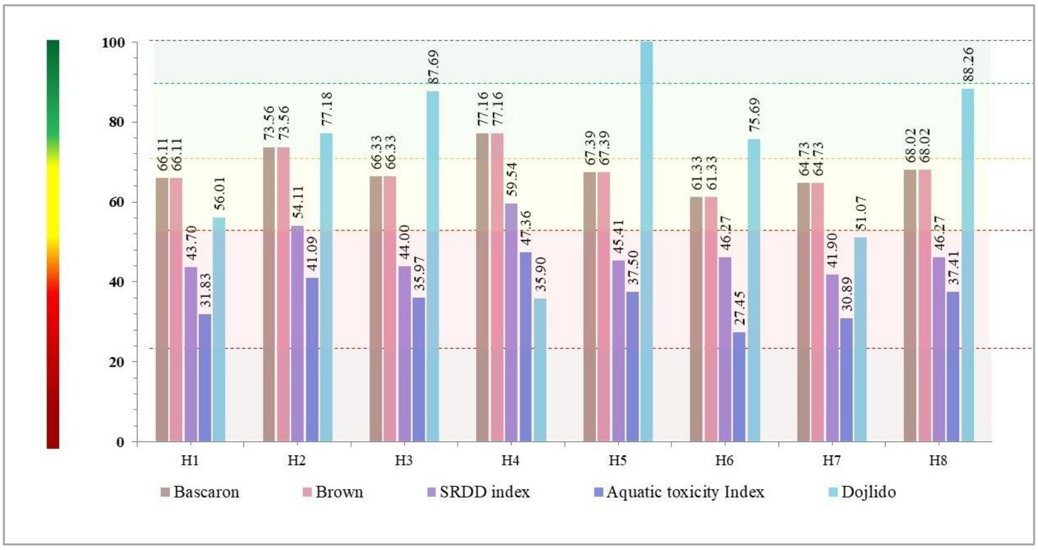

Figure 4. 11 WQI Values of Harsola

4.5 Entropy-weighted water quality index values:

The Entropy-Weighted Water Quality Index (EWQI) values for five villages—Gokanya, Simrol, Borkhedi, Memdi, and Harsola, indicate extensive spatial variation in water quality status as shown in Table 4.11. Gokanya and Simrol show EWQI values between 63.77 and 104.45, indicating them to be in the category of "good to average" quality. Strikingly, the peak EWQI (104.45) of Gokanya indicates a change towards the average class, indicating moderate contamination, whereas Simrol has comparatively better status, with most of the values falling short of 100. Borkhedi is seen to have increasing EWQI values, especially reaching 117.60, which puts some regions of the village in the "average" water quality class, probably due to the higher organic load and suspended solids found previously. More troubling are the results in Memdi and Harsola, where EWQI levels go over 150 in several samples—152.0 in Memdi and 124.14 in Harsola, emphatically classifying them within the "poor" and on the verge of being "extremely poor." These are in accordance with previous WQI model predictions that Memdi (M6, M7) and Harsola (H1, H5) were severely affected by high BOD, COD, and turbidity. The entropy-weighted method places greater emphasis on highly variable parameters, thus exaggerating the influence of low-performing variables. The uniform trend of elevated EWQI levels in Memdi and Harsola calls for immediate attention, as water for drinking from these areas could be unhealthy to consume without treatment. Moreover, entropy-based weighting guarantees objectivity, making the EWQI model suitably useful in rural water quality monitoring where limited resources necessitate data-driven planning.

Table 4. 11 Entropy-weightage water quality parameters for all villages

Parameters	Weightage (%)				
	Gokanya	Simrol	Borkhedi	Memdi	Harsola
pH	5.32	2.82	7.89	7.95	8.07
Turbidity	6.05	2.31	5.57	5.94	5.69
Free Chlorine	6.18	2.29	5.27	9.51	5.39
Alkalinity	6.15	2.79	5.94	1.38	6.07
Hardness	6.07	2.75	7.05	5.54	2.15
DO	3.84	3.79	5.68	7.31	5.82
BOD	8.43	2.43	5.90	6.93	6.04
COD	4.88	4.45	7.95	4.62	8.13
TSS	6.55	3.81	5.32	6.26	5.44

VSS	2.51	3.84	2.63	2.97	2.69
Mn	0.00	2.24	0.00	0.00	0.00
Zn	6.18	3.78	0.00	0.00	0.00
Fe	6.18	3.98	9.21	6.44	9.48
Ni	0.00	2.24	0.00	0.00	0.00
Cd	0.00	0.00	0.00	0.00	0.00
Na	6.83	3.57	7.67	6.72	7.84
K	6.38	2.27	5.51	4.62	8.39
Ca	2.99	4.80	7.90	6.10	8.08
EC	5.71	2.79	0.00	0.00	0.00
Cr	0.00	0.00	0.00	0.00	0.00
Pb	0.00	0.00	2.57	5.18	2.63
F	3.28	7.53	1.70	2.80	1.74
Cl-	4.02	17.63	3.07	5.42	3.14
NO3-	2.39	17.84	3.14	4.25	3.21

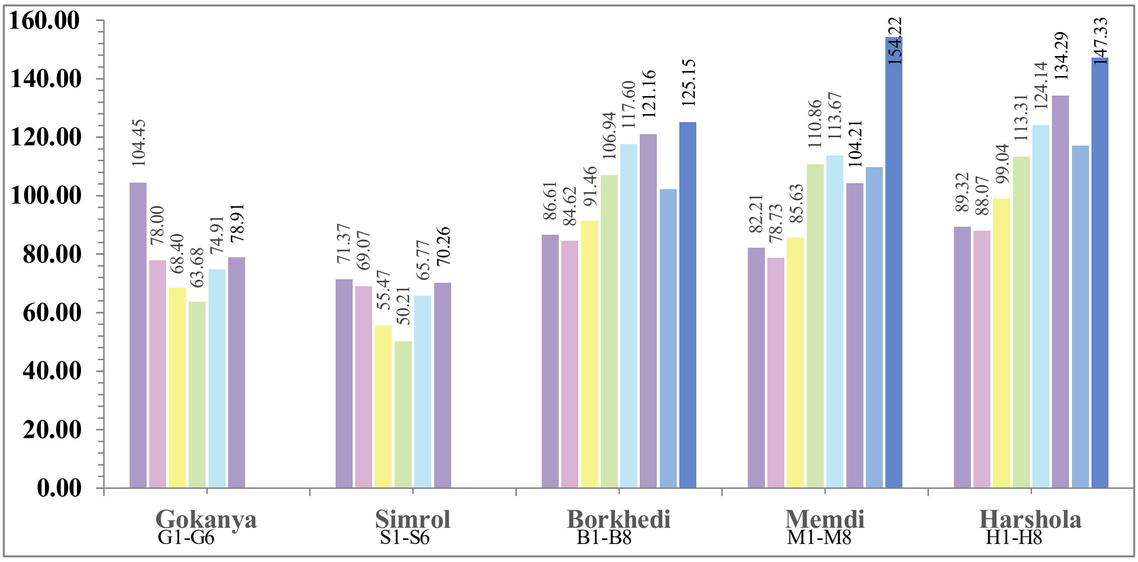

Figure 4. 12 EWQI Values of villages

4.6 Result of Sensitivity Analysis:

4.6.1 Borkhedi

Sensitivity analysis of Borkhedi presents remarkable differences in the sensitivity of various water quality parameters on WQI models. Compared to all models, SRDD has the maximum mean sensitivity (7.94) with a high standard deviation (8.75), which reflects that its ratings are significantly sensitive to each parameter's change, especially parameters such as

COD, BOD_5, and EC. By contrast, the lowest sensitivity (mean = 1.90) is evidenced through the Dojlido model, indicating its aggregation structure is more inert or resistant to single parameter deviations, but has the possibility of missing localized peaks of pollution. Aquatic Toxicity, Bascaron, Brown, and Entropy models give moderate and uniform sensitivity (mean ≈ 4.17), indicating an equal response to parameters. The variation in sensitivity of all water quality parameters is shown in Figure 4.13. They illustrate the significance of choosing suitable WQI models depending on regional contamination patterns as well as the desired sensitivity of the evaluation.

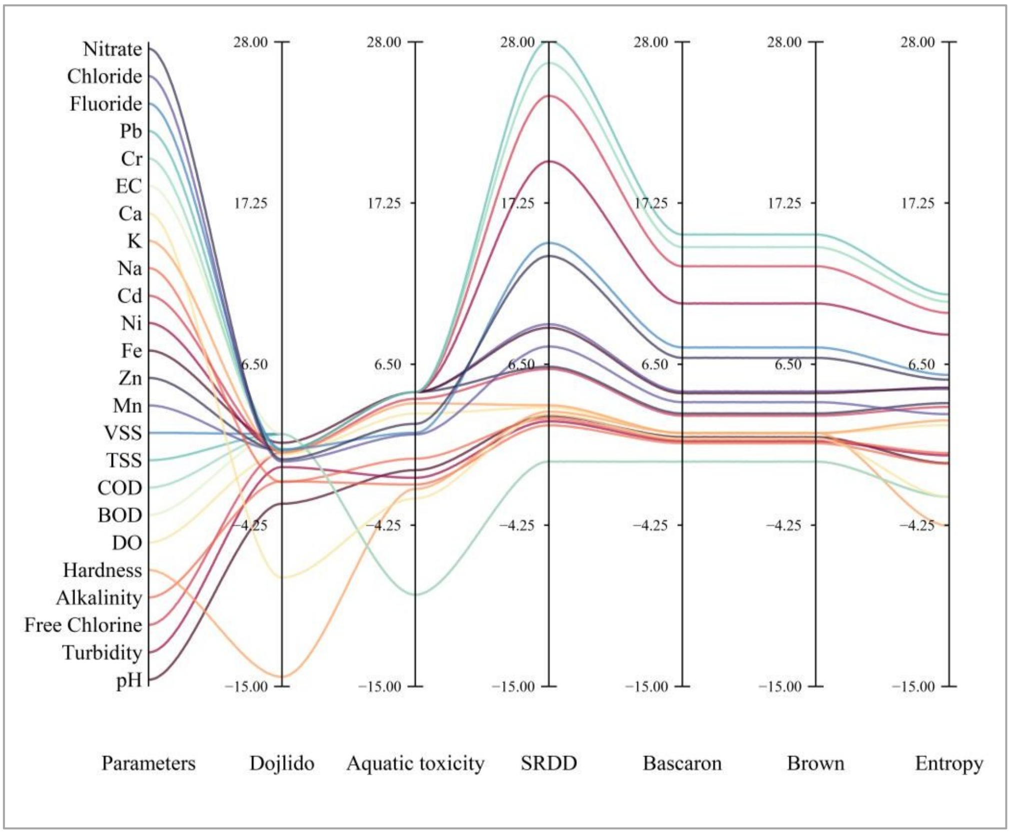

Figure 4. 13 Sensitivity Analysis of Water Quality Parameters in Borkhedi

Table 4. 12 Sensitivity Analysis of all WQI Models in Borkhedi

WQI Models	Mean	STD
Dojlido	1.90	3.06
Aquatic toxicity	4.25	2.80
SRDD	7.94	8.75

Bascaron	4.17	4.68
Brown	4.17	4.68
Entropy	4.17	4.76

4.6.2 Gokanya

Sensitivity analysis of Gokanya reveals that among all the models, SRDD is the most sensitive (mean = 7.96, STD = 8.27), which indicates its high responsiveness to parameter changes, particularly nitrate, EC, and COD. The Dojlido index, having a low mean (2.29) and low standard deviation (1.79), is still the least sensitive, which reaffirms its poor ability to reflect parameter variability. Moderate and consistent sensitivity is seen in Bascaron, Brown, and Entropy models (mean = 4.17), revealing a balanced reaction to both stable and variable water quality conditions. Aquatic Toxicity Index (mean = 3.64) shows intermediate behavior, with factors such as VSS and fluoride having more significant impacts on its output. The variation in sensitivity of all water quality parameters is shown in Figure 4.14. Generally, SRDD appears to be the strictest model, and Dojlido can potentially underrepresent the risks of contamination in this area.

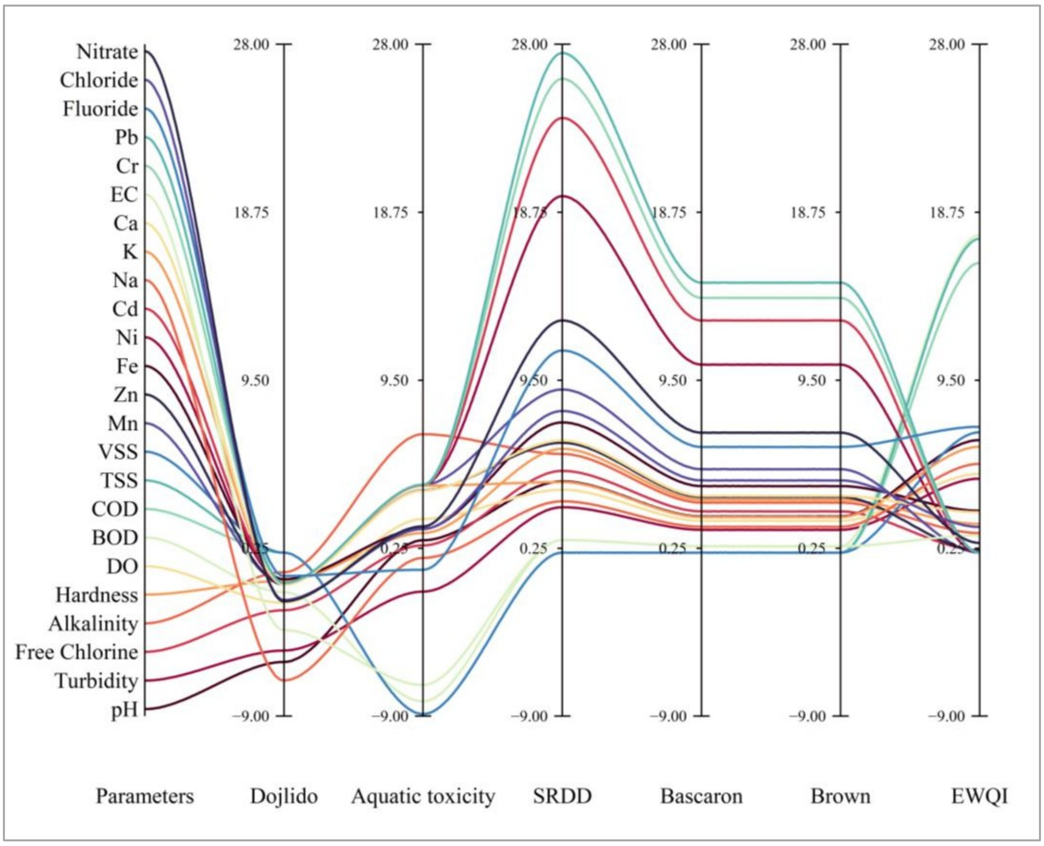

Figure 4. 14 Sensitivity Analysis of Water Quality Parameters in Gokanya

Table 4. 13 Sensitivity Analysis of all WQI Models in Gokanya

WQI Models	Mean	STD
Dojlido	2.29	1.79
Aquatic toxicity	3.64	2.72
SRDD	7.96	8.27
Bascaron	4.17	4.45
Brown	4.17	4.45
Entropy	4.17	5.45

4.6.3 Simrol

The sensitivity analysis of Simrol shows that the SRDD model once more proves the most sensitive to the variation of individual parameters, with a mean value of 6.98 and a high standard deviation of 8.84.

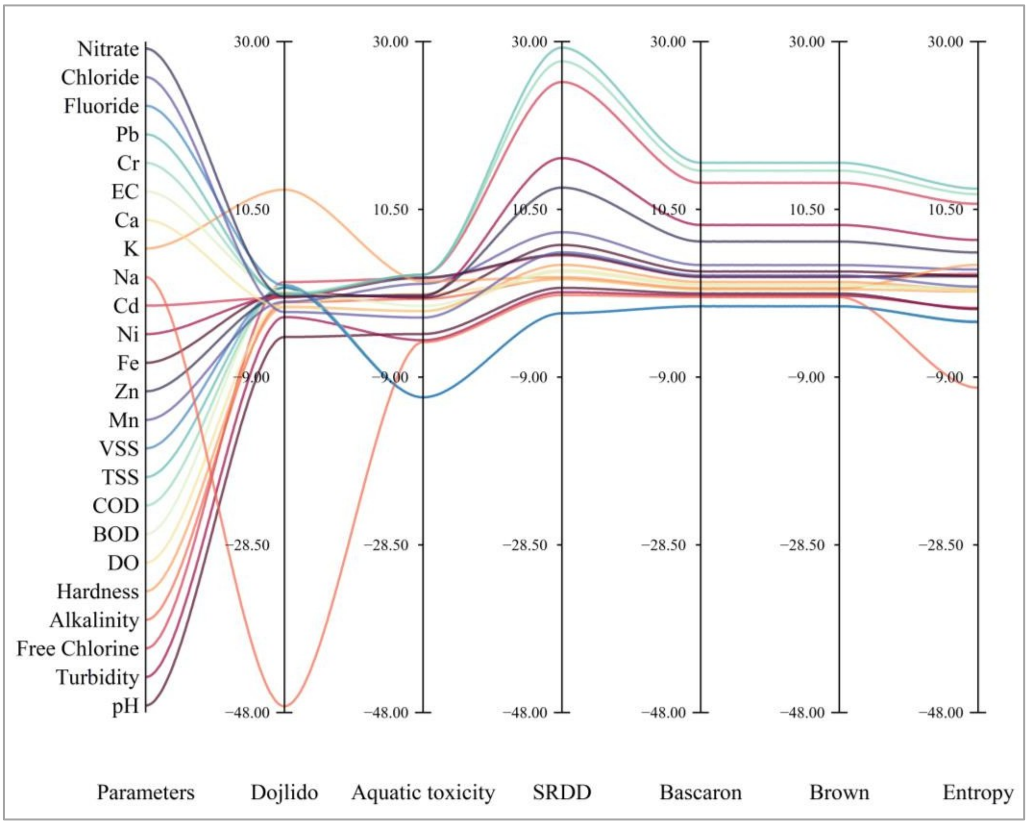

Figure 4. 15 Sensitivity Analysis of Water Quality Parameters in Simrol

The variation in sensitivity of all water quality parameters is shown in Figure 4.15. To the surprise of all, the Dojlido model, although with a moderate mean value of 3.51, displays maximum variability (STD = 9.66), and hence it is less predictable in its parameter-specific sensitivity. Models such as Bascaron and Brown are still moderate and consistent in behaviour (mean = 3.75), whereas Entropy-based WQI has a little more sensitivity (4.17), possibly because data-driven weight allocation enhances parameters such as COD and heavy metals. The Aquatic Toxicity Index (mean = 3.98) is conservative and responsive in its behaviour and is sensitive to organic and nutrient indicators. The entropy, Brown, and Bascaron consistency provide a stable model for frequent monitoring.

Table 4. 14 Sensitivity Analysis of all WQI models in Simrol

WQI Models	Mean	STD
Dojlido	3.51	9.66
Aquatic toxicity	3.98	4.08
SRDD	6.98	8.84
Bascaron	3.75	4.73
Brown	3.75	4.73
Entropy	4.17	5.69

4.6.4 Memdi

The sensitivity analysis of Memdi indicates that the SRDD model is most sensitive to parameter changes, with a mean sensitivity of 7.97 and a standard deviation of 8.30, being heavily dependent on parameters such as COD, TSS, and VSS. The variation in sensitivity of all water quality parameters is shown in Figure 4.16. Conversely, the Dojlido model has the lowest sensitivity (mean = 1.46), which means that it is least sensitive to variation in individual parameters and can potentially mask localised pollution. Bascaron, Brown, and Entropy models have the same mean values (4.17), but Entropy is marginally more variable (STD = 5.10), meaning moderate sensitivity with a bit of parameter-specific spikes. The Aquatic Toxicity Index is intermediate with a mean of 3.67, indicating moderate sensitivity to organics and heavy metals. SRDD model sensitivity to the extremes emphasises it as most diagnostic of contaminated sites, such as Memdi, whereas Dojlido is too conservative and may be underestimating risks.

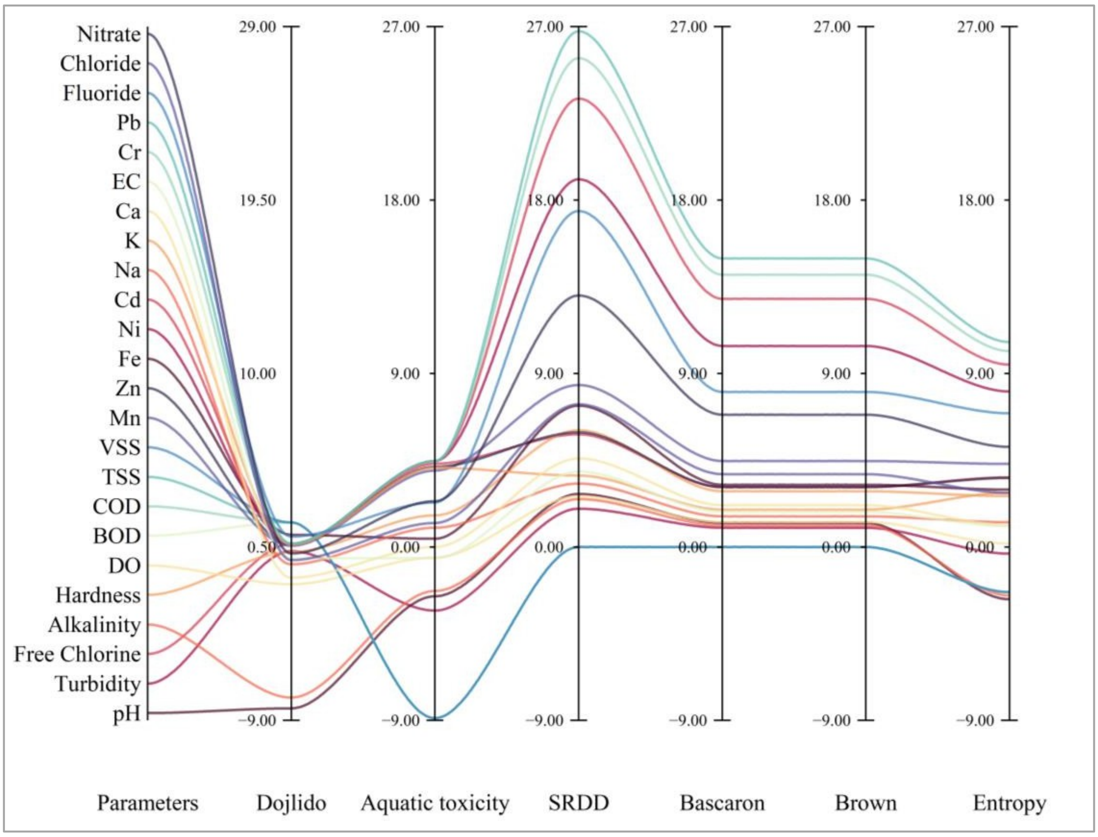

Figure 4. 16 Sensitivity Analysis of Water Quality Parameters in Memdi

Table 4. 15 Sensitivity Analysis of all WQI models in Memdi

WQI Models	Mean	STD
Dojlido	1.46	2.11
Aquatic toxicity	3.67	2.79
SRDD	7.97	8.30
Bascaron	4.17	4.59
Brown	4.17	4.59
Entropy	4.17	5.10

4.6.5 Harsola

Harsola's sensitivity analysis indicates that the SRDD model is most sensitive (mean = 7.91, STD = 9.16), as it has a robust response to changes in individual parameters like COD, EC, Cr, and turbidity. The variation in sensitivity of all water quality parameters is shown in Figure 4.17. The Dojlido model, having the lowest mean value of 2.81 and STD of 5.17, demonstrates very little fluctuation and hence might be underestimating the effects of certain pollutants. Moderate and virtually equal sensitivity scores are found in Bascaron, Brown, and Entropy models (mean ≈ 4.17), suggesting a stable but less variable response profile. Notably, the Aquatic Toxicity Index reveals a different pattern of moderate sensitivity (mean = 4.91), but with a lower standard deviation, indicating a specialized reaction to a subset of influential factors such as nitrate and heavy metals.

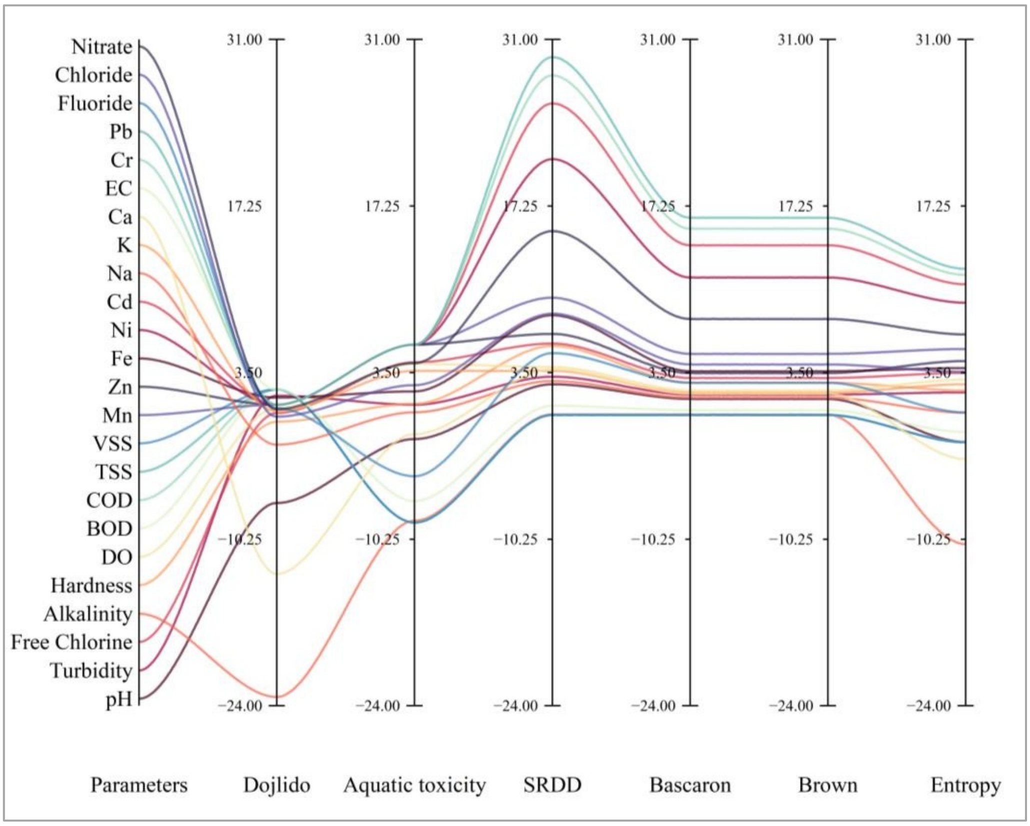

Figure 4. 17 Sensitivity Analysis of Water Quality Parameters in Harsola

Table 4. 16 Sensitivity Analysis of all WQI Models in Harsola

WQI Models	Mean	STD
Dojlido	2.81	5.17
Aquatic toxicity	4.91	2.79
SRDD	7.91	9.16
Bascaron	4.17	5.02
Brown	4.17	5.02
Entropy	4.17	5.16

CHAPTER 5

CONCLUSIONS AND FUTURE SCOPE

5.1 Conclusions:

Rural water quality in five villages of Indore was assessed through a study evaluating 24 physicochemical and heavy metal parameters through different Water Quality Index (WQI) models. Several contaminations were reported, with fluoride as high as 2.4 mg/L, and organic pollutants and heavy metals such as Mn, Zn, Fe, and Ni identified in many samples. The Dojlido Index produced the highest values of WQI (almost 100) in areas such as Borkhedi (B1), Memdi (M5, M8), and Harsola (H5), but it grossly overestimated water quality, not detecting major contamination. The SRDD model was best in indicating the maximum sensitivity (7.97 in Memdi), successfully raising alarms on toxic pollutants, but its variability lowered its reliability. Conversely, the Bascaron, Brown, and Entropy-weighted WQI models exhibited moderate sensitivity and more realistically tracked field-measured conditions and were thus appropriate for rural use. The Aquatic Toxicity Index generated unrealistically low results at many sites (e.g., 25.60 at site M6), resulting in excessively negative assessments not consistent with potability criteria. West Java and Dinius models yielded close-to-zero WQI values at all locations, validating their structural inappropriateness for groundwater-based rural situations. Thus, Bascaron, Brown, and Entropy-based indices are advised for field-based, context-specific, and sustainable rural water quality monitoring in India.

5.2 Future Scope

(a) **Expansion of Sampling Base:** Additional incorporation of villages and seasonal data (pre-monsoon, monsoon, post-monsoon) would increase the spatial-temporal resolution and **robustness of generalizability.**

(b) **Integration of Microbiological Indicators:** Since the lack of disinfection and sanitation infrastructure was observed in the study, the addition of coliform and E. coli parameters is critical for a comprehensive evaluation of drinking water safety.

(c) **Machine Learning for Weight Optimization:** Future research may consider the hybrid weighting schemes of AHP, Entropy, and ML-based optimization (e.g., Random Forest, PCA-AHP) for adaptive index models.

(d) **Region-Specific WQI Development:** The findings of this study can form the basis of a new composite WQI specifically for central Indian rural settings, balancing scientific precision and usability.

(e) **Uncertainty Quantification:** Additional enhancement of uncertainty analysis through stochastic simulations can quantify the influence of measurement errors and data gaps on WQI results.

(f) **Policy Translation and Community Involvement:** Findings can be translated into decision-support tools for rural water boards and Panchayats. Locally adaptable participatory structures (e.g., MAGs – Management Action Groups) could also be activated to co-monitor and co-manage water safety.

APPENDIX

Figure A. 1 Collecting Water Samples from Different Locations

Figure A. 2 Instruments used in the Environmental Lab at IITI

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