Investigation and Comparative Assessment of Surface Water Quality for Drinking Purposes by Using Relief Algorithm, GIS, and Machine Learning : A Case Study of Mahanadi River Basin, Odisha (India)

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Abstract: Surface water is the best source of drinking water available. However, climate change, over-pumping, and a variety of contaminants have all led to the depletion of this valuable resource. Conducting surface water quality assessments for home usage, especially drinking water, is essential to safeguarding human health and effectively managing resources. In this study, this work has highlighted an evaluation of surface water quality of river Mahanadi, Odisha, for drinking purposes using Relief Algorithm (RA) based WQI (RA-WQI), with reliability-based MLs (Machine Learning) such as Weight of Evidence (WOE) have been employed. For this, water samples from 19 locations were taken for a period of 2018-2023, to test 20 physicochemical parameters in the selected sampling sites. The findings indicated that although pH changes, the water is alkaline and its value spanned from 7.73 to 7.9. The concentration of coliform and TKN is found to be higher at all locations. The highest levels of Cl^- and SO_4^{2-} are located close to the downstream area. Based on the results, anions and cations are observing a shift in the trend, i.e., $Fe^{2+} > B^+$ and $Cl^- > SO_4^{2-} > NO_3^- > F^-$ respectively, throughout the occupied duration. Further, the calculated RA-WQI revealed that 63.16% belong to poor water quality while 31.57% of sites come under the zone of excellent water. However, 5.26% of samples indicated an unsuitable water class. The analysis primarily revealed that at 8 samples, the main cause could be deterioration of domestic water, illegally dumped municipal solid waste, and agricultural runoff were the leading sources causing adulteration of the river's water quality. As a result, a renowned ML models, such as WOE, were adopted and it suggests location SP-(9) was the most polluted in comparison with other locations, followed by SP-(8), (19), and (2) respectively. Following this, the analytic findings also suggests from the highest RA-WQI values that consists of 488, 243, 277 and 285 at this location. However, it was relevant that the degree of pollution at these stations was more closely linked to a wide range of expanding human activities, such as excessive water use, fertilizer effects, agricultural runoff, and industrial activity in and around the river corridor. According to the drinking water quality indices, the surface water in the area under investigation is classified as suitable for human consumption. Thus, the results illuminate the preservation and distribution of drinkable and irrigable surface water supplies, and provide decision-makers with a valuable resource for implementing successful surface water protection strategies in the area under study.

Keywords: Surface water, Relief, WOE, Domestic, Anthropogenic, Coliform, TKN

1. Introduction

In recent years, the world has seen a shortage of surface water resources as a result of urbanization and population growth, exposing water supplies to declines in both quantity and quality [1]. Unfortunately, in India, the misuse of fertilizers and agrochemicals that seep into the aquifer system, along with overexploitation without a balanced recharge, are causing the degradation of surface water to accelerate [2]. Besides this, recent anthropogenic activities significantly boost the rate at which nitrogen is cycled between the atmosphere, soil, water, and living things [3]. As a result, examining the agricultural water quality is necessary to lessen the detrimental effects on drinking. The sustainable development of humankind may be in jeopardy due to the current imbalance in availability and increase in demand for water resources. As a result, water management strategies have been established, primarily depending on surface water and steady runoff [4]. Numerous studies have employed techniques including categorization, correlation analysis, and time-series numerical analysis of collected data to evaluate the quality of water [5]. But evaluating water quality using time-series numerical analysis on long-term collected data necessitates a laborious and drawn-out method for organizing the data. In the end, these techniques offer the benefit of not requiring specialized understanding of the environment or water quality. Therefore, the water quality index (WQI) is regarded as a mathematical instrument that greatly reduces those data sets and yields a single classification value that characterizes the level of pollution or the water quality condition of water bodies

[6]. In order to more efficiently and precisely depict water quality, these measures have undergone various development and improvement processes. Water quality is thus reduced to a single number for thorough evaluation, which makes it easier for the general public and decision-makers to comprehend water quality. For example, eclipsing and ambiguity are WQI problems that can be solved by combining geometric and additive techniques. Initially, experts assign the weights based on their real-world experiences [7]. Additionally, their preferences used to differ, which added uncertainty to the conclusions of the evaluation of the water quality. To solve this subjective issue, Relief Algorithm (RA)-based weights have become a valuable method that leverage information entropy to give water quality criteria weights [8]. This mechanism is applied to assess the importance of every response without taking the decision maker's option into account. The fundamental approach is to use the following two fundamental ideas to establish the indicators' objective weights: Standard deviation is used to represent contrast intensity, which shows the value difference between several assessment schemes of the same index; and the basis for any conflict amongst assessment of indicators is, the connection between them [9]. However, such methods ignore the randomness, complexity, and nonlinearity in environmental challenges as well as the spatial and temporal fluctuations of surface water components [10]. In comparison to those subjective assessment techniques, information based on RA has greater and stronger objectivity and correctness, which helps to explain the outcomes [11]. This approach starts with establishing goals, then computes the normalized option matrix and assigns an index weight based on how much each index value varies. This helps to prevent deviations brought on by human factors. On the other hand, it advocates as a class of correlation-based techniques that rely on analytical testing of the decision matrix to ascertain the data present in the criteria that govern how criteria weights are assessed [12]. In context of spatial mapping, Geographical Information System (GIS) software is employed to create different themed spatial maps that analyze variations in surface water quality [13] The usage of sample points from disparate places in GIS analysis has so increased recently in order to generate and obtain an ongoing parameter via data gathered from the measured parameters in order to forecast figures for each location in the landscape [14]. The following authors used GIS tools to analyze the potential for surface water worldwide. For example, a renowned author namely, [15] made use of an analytic hierarchy (AH) process, utilizing the implementation of GIS, to examine the WQ in Central Anatolia, Turkey. One additional researcher, specifically, [16], implemented the restricted irrigation WQI, in alongside GIS, to assess surface water's potential for irrigation in West Pampa Plain, Argentina. However, [17] also evaluated the irrigation water and used GIS in the Sivas Province, Turkey, and discovered that the majority of the water samples are in the appropriate irrigation zone. Consequently, these studies collectively indicated that the integration of remote sensing and GIS facilitates a versatile and intuitive application that aids in surface water treatment strategy and choice-making by means of spatial evaluation, manipulation, and representation [18]. The spatial variation maps in this study were obtained by means of Inverse Distance Weighted (IDW) interpolation techniques. The IDW method It was selected because, using variogram analysis, a simple linear weighting of the variability among adjacent points may be used to forecast the value at the unsampled location [19]. As was already indicated, the RA approaches suffer from a great deal of complexity in addition to increased time consumption and computing demands. Therefore, for numerous decades, academics have employed these machine learning algorithms to determine vulnerable zones by weighing multiple thematic layers in order to overcome this constraint. Meanwhile, integrating Multi-Criteria Decision-Making (MCDM) and Machine Learning (ML) analysis with GIS, encourages the use of an economical and useful method for managing geographic data [20]. So, this method has been effectively used to accurately forecast the qualities of surface water quality. While earlier research suggested that several machine learning models performed exceptionally well, it did not look at how well these models could be used for feature selection [21]. Therefore, when figuring out the specific relationships between the quality metrics and the measurement sites, the current study concentrated on using a Weight of Evidence (WOE) algorithm, for the optimal decision for the input variables and subsequently, may forecast measures of water quality [22]. Hence, by analysing the water quality with this program, it is frequently used to forecast various processes. This indicates that WOE outperforms standard methods in terms of accuracy while working with constrained parameters, which is a key feature of machine learning. This makes it necessary for this approach to evaluate the locations overall by taking into account both the chemical and physical factors and giving judgments top priority when there are unforeseen circumstances [23]. In other words, [24] created this approach, which combines the weighted sum and exponentially weighted product techniques. This is precisely the results from several experts showed that the discretization by regression strategy for drinking indices performs better when the RA algorithm is used. Therefore, reviews in the literature

clarify the implications of WOE-based machine learning models for enhanced feature selection in engineering issues. This creative method, which represents one of the earliest attempts at an integrated strategy for evaluating of surface water quality, is being used in the current inquiry. Although they were limited to a single watershed, data redundancy, and a certain kind of data stochasticity, old approaches produced accurate predictions of water quality. Because this strategy is primarily focused on a single problem-solving approach in any location, there is a research gap that has to be filled by creating a novel integrated approach, which this study demonstrates to be effective [25]. The most reliable method for handling a complex non-linear relationship with components in prediction and solving the global optimization problem is the WOE approach. This helps overcome new problems. In addition, numerous investigations have demonstrated the study area's susceptibility to pollution, especially nitrate and coliform. To map the surface water quality in the researched area, this study was started. Moreover, nitrate contamination of surface water is a widespread issue that has raised significant concerns globally. This is explained by its negative impacts on both the environment and human health. Additionally, this study uses these two new models to assess the annual and regional variations in physicochemical factors that impact water quality and to identify the drinking-water-vulnerable zones in surface water quality. Thus, the current investigation was started with the following particular objectives in mind: (1) evaluation of the drinking water quality of the surface water using RA-WQI, and (2) exhibiting the efficiency of the RA-WQI, which establishes the weight of the criteria, and WOE, which scores the possibilities and chooses the best alternative. The above-mentioned goals will make it easier to conceptualize whether the hydro-chemical mechanisms within the river basin are affected by climate change. Therefore, the general background of water quality that urban planners need to take into consideration for good planning and water management in Odisha will be provided by this both qualitative and quantitative evaluation of water resources.

1.1. The motivation for the work

Water is the main component of planning for smart cities. Here, it is an innovative strategy by Government of Odisha, to incorporate environmentally friendly urban design. However, one important component of the smart city strategy is ensuring that residents have access to clean, safe water. Due to its location on the Bay of Bengal shore, the basin's downstream port faces the threat of saltwater intrusion into the freshwater aquifer.

1.2 Structure of the paper

Section 1 is the broad overview that discusses the declining water quality and depletion, as well as the river basin's introduction. Section 2 explains the area for study; Section 3 explains the procedures needed to perform physicochemical analyses. Then finally, Section 4 explains about Results and Discussions part. In addition, Section 5 wraps up the entire chapter and offers recommendations for development.

2. Study Area

The studied area namely, Mahanadi River System (MRS), is the biggest river in the State of Odisha, with an extensive history of agricultural irrigation and fishing. It provides household water for the major towns. Considering an average yearly rainfall of between 1200 and 1400 mm, the area covered is classified as sub-tropical. The catchment's geographical position primarily affects the climate in relation to the Bay of Bengal [26]. However, the catchment is distinguished into three smaller regions, namely, the Upper, that contains around 21.34%, Middle region covers up to 37.16%, and subsequently, 41.5% is coveted under Lower Mahanadi group. Typically, the lower basin encompasses an area of approximately 57960 Km^2, while the basin's entire capacity for live storage is thought to be around 14.244 BCM. Out of which, 12.799 BCM of work is being accomplished, and rest 1.465 BCM, is currently being going on. This corresponds to 28.4% of the 75% reliable potable water and 21.32% of the mean annual inflow. Consequently, the river's entire length is approximately 851 Km, that embraces an area of approximately 141,600 Km^2. This study region is located between the geographic coordinates of 81°45’E to 87°00’E and 19°30’N to 23°15’N, and is known as the third largest in the Indian Peninsula. Here, Agriculture and forest are the two primary land uses in the basin, and big and medium-sized projects provide the substantial irrigation infrastructure that supports them. Also, with a mixture of industrial and subsistence farming techniques led by rice growing, it is mostly an agricultural region. Even though there are spells of rain with different lengths and intensities, the monsoon season, which starts in June and lasts until October, accounts for more than 90% of the total precipitation. This river consistently has stagnant water in it from January to May of each year, which contributes to the buildup of pollutants in the surrounding area [27]. The basin's average temperature is recorded to range from 24°C to 27°C, while the crop namely, rice predominates the cereals crop group, subsequently, pulses within the basin. The typical kinds of soil include, mixed-red and black soils, in addition to red and yellow soils. As demonstrated in Figure 1, the agricultural land renders up roughly 54% of the research area, followed by urban that considers about 24%, barren land corresponds to 10%, and finally, 20% accounts for forest lands. However, it is advised that the central Odisha regions that constitute up the basin, which possess smaller-scale rainfed farming systems and be more densely wooded.

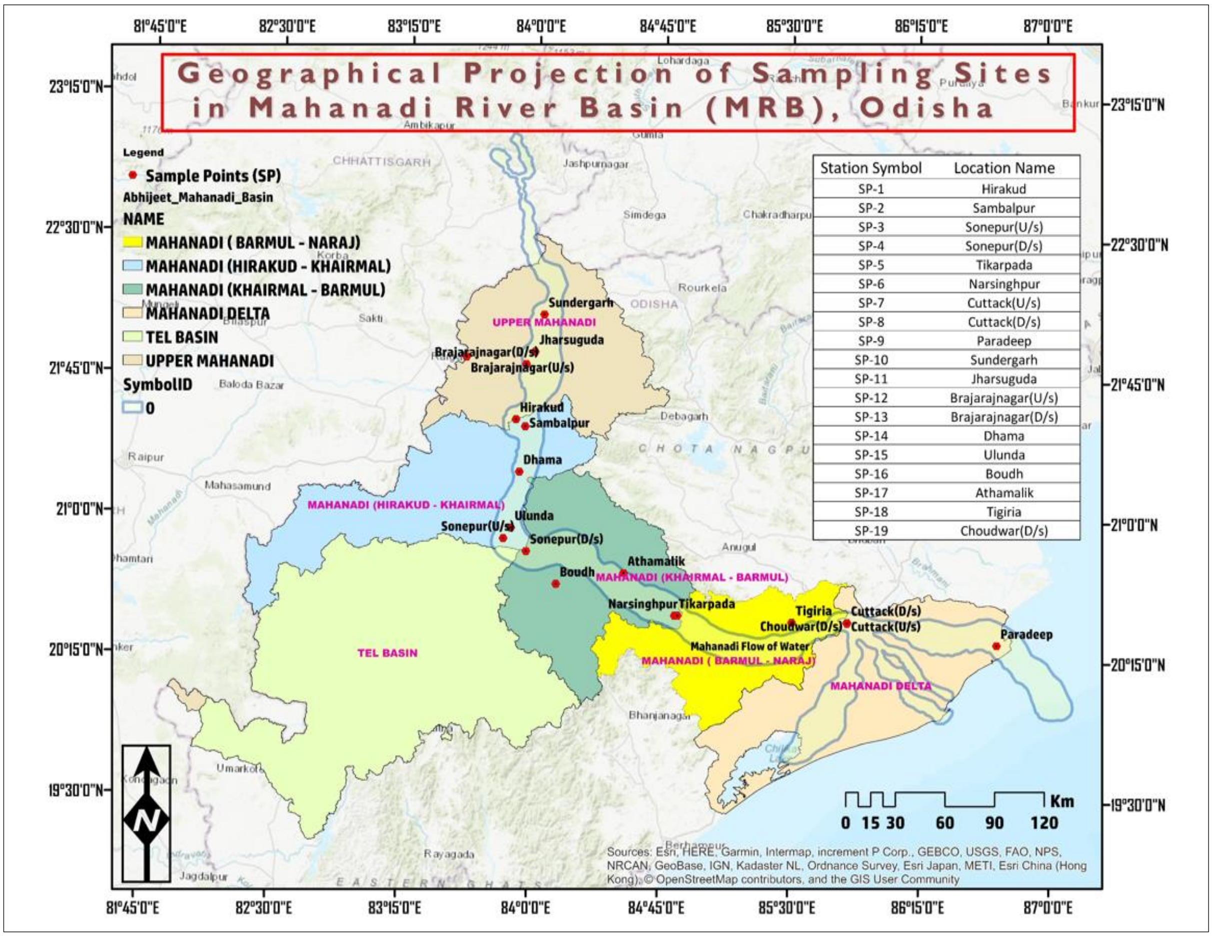


Figure 1. Sample and study area location map

3. Materials and Methods

3.1 Sampling, Field Work and Laboratory Chemical Analyses

Twenty surface water representative samples were gathered from 19 locations in the studied area for a period of 5 year (2018-2023). The locations of the stations were identified with a handheld Global Positioning System (GPS). Further, chemical analysis was carried out using standard analytical procedures [28]. The sampling bottles were cleaned and let to soak in HCL prior to gathering the samples. The bottles were carefully sealed after being collected and stored in the refrigerator at 4°C. The model campaign includes 20 variables namely: pH, BOD (biochemical oxygen demand), DO (dissolved oxygen), TC (coliform), NH_3-N (ammoniacal nitrogen), TDS (total dissolved solids), TH (total hardness), Alkalinity, COD (chemical oxygen demand), Chloride (Cl^-), Sulphate (SO_4^{2-}), Iron (Fe^{2+}), Fluoride (F^-), Boron (B^+), TSS (total suspended solids), electrical conductivity (EC), free ammonia (Free NH_3), TKN (total kjeldahl nitrogen), SAR (sodium adsorption ratio), and TH (total hardness). However, EC (Electrical conductivity), DO (dissolved oxygen), pH, and TDS (total dissolved solids) were gauged using in-situ by a potable multi meter, while the Cl^- (Chloride), Sulphate (SO_4^{2-}), Fluoride (F^-) and finally, Nitrate (NO_3^-), is evaluated by adapting Spectrophotometric technique. Alkalinity, Total hardness (TH) were analysed by titration methods. A total of 2 metals, namely iron (Fe^{2+}) and boron (B^{+}) were analysed by ion chromatograph (IC). The remaining tests of parameters were conducted according to the bureau of Indian standards. In addition, observations that lacked any of the data were deleted. The goal is to ensure that the characteristics and conditions of the subsurface environment are accurately depicted in the water samples that were gathered. The procedures addressed by American Public Health Association (APHA) were employed in both laboratory and field analyses. The analytical uncertainty is less than 4% in cases when three separate samples were analysed. Afterwords, it is evident that the requirements for water purity were double-checked, using Ion Balance Error (IBE), because of their precision in analysing chemical data, and is often gets observable in milliequivalent per litre (meq/L). The obtained value of IBE was used to assess the accuracy of the analysis, demonstrating that it could be repeated with error limitations of 10%.

3.2 Relief algorithm (RA)

This algorithm suggested by [29], is a popular feature selection technique that assesses each feature's significance in a dataset by determining how well it can differentiate between various groups. The stages involved in computing the results include identifying and prioritizing the criteria for making decisions, estimating the coefficients for each criterion, determining the relative relevance of each criterion, and recalculating the weight, and finally, determination of the relative weight (W_i), are addressed by [30]. Nonetheless, this method was used to examine the dataset of many variables in a trustworthy manner at various sampling locations. Finding the optimum input factors to explain the dependent variable is necessary for the construction of prediction models for any process or phenomenon. In the current study, a relief method has been used to choose the optimal combinations of input variables. Thus, the primary goal of this review was to develop a straightforward WQI calculation process that can be used to determine the quality of surface and subsurface water using machine learning techniques, with less effort and greater accuracy. This approach also involves considering the spatiotemporal range of the water's purity of a water source [31]. A further consideration for choosing the optimal input parameters, is the data's dimensionality reduction to make handling it easier. Furthermore, it proposes a grading system that offers the combined impact of every chosen water quality measure on the total water quality. It is necessary to select adequate input parameters, nevertheless, in order to account for the response variable's variability. As a result, the way this method functions are by giving each feature a weight determined by how well it can distinguish between similar occurrences in the features space. Subsequently, the features are ranked according to their estimated weights, with the most relevant features being those with the highest ranking. The calculation of the index scores in RA-WQI method was differentiated into following four categories and considered as excellent (<50), good (50-100), poor (100-200), very poor (200-300) and >300 as unsuitable water class. Following this on the basis of [32], the concentrations that were observed were entered into the designated mathematical expression for each parameter., given by [29], in order to find the index score. Additionally, the relief algorithm can increase the efficiency and accuracy of machine learning models by choosing the most pertinent features, especially when the original dataset has a large number of features.

3.3 Weight of Evidence (WOE) Model

As previously recognized, the enormous complexity of WOE approaches is an issue in addition to requiring additional time and computing effort. However, this suggested method aggregates the weights in two ways and employs a comparability sequence [33]. Because of this, once the obtained data has been normalized, survey site ratings may yield trustworthy results. Conventional techniques, on the other hand, produced accurate predictions of water quality but were limited to a certain watershed, data redundancy, and a particular kind of data stochasticity [21]. Hence, to get over this limitation, The current investigation focused on using a Weight of Evidence (WOE) algorithm, to choose the optimal input parameters, which would then allow for the prediction of water quality indices [34]. So, when calculating a WQI score, issues like rigidity, ambiguity, and eclipsing will always arise, but these issues can be resolved with this method [33]. Therefore, the WOE approach referred as the most reliable method for handling a complex non-linear connection with prediction parameters and for solving the global optimization problem. In general, it tells the proportional power of the disparity from the comparable sequence in addition to the standard multiplication rule [23]. While earlier research suggested that several machine learning models performed exceptionally well, it did not look at how well these models could be used for feature selection. The theoretical basis of assessment processes and the universal language utilised to pinpoint and address complex water concerns are therefore crucial to the effectiveness of the methods recommended by this methodology [24]. Therefore, the literature of reviews illustrates the manner in which WOE-based machine learning models can be used to optimize feature selection in engineering challenges. This method has been effectively utilized to accurately forecast the qualities of surface water quality. Furthermore, because the quality of the database is a major factor in determining how well an algorithm predicts the target variable, researchers may find it challenging to choose the best machine learning (ML) algorithm for a given problem. However, the RA method is expensive, time-consuming, and laborious [35]. This restriction from the studies that were reviewed, encouraged us to utilize the feature selection method by WOE, for creating forecasting models for assessing the quality of the water [25]. Meanwhile, selecting the right machine learning algorithm may be difficult due to this ambiguity. Numerous studies on this topic, both nationally and internationally, have used ML techniques to predict WQI utilizing all of the input factors. This indicates that WOE outperforms previous methods in terms of accuracy while utilizing fewer parameters, which is a key feature of machine learning [36]. It has been noted that the discretization by regression strategy for drinking indices performs better when the RA algorithm is used, according to results from various specialists. Once the options and associated criteria have been established, the processes listed below are verified in order to answer a decision problem, as shown in Figure 2.

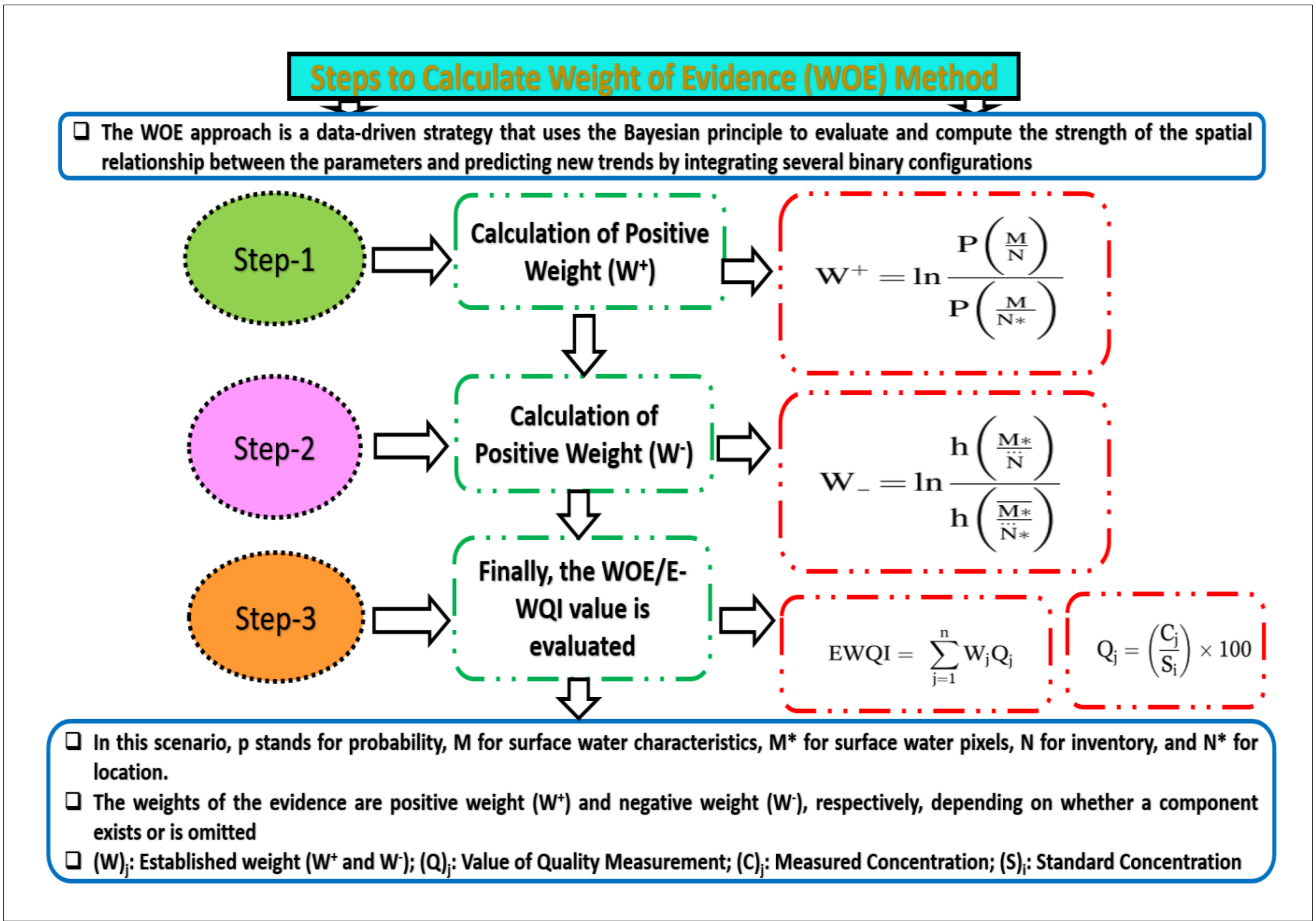


Figure 2. Schematic representation of WOE Model

4. Results and Discussions

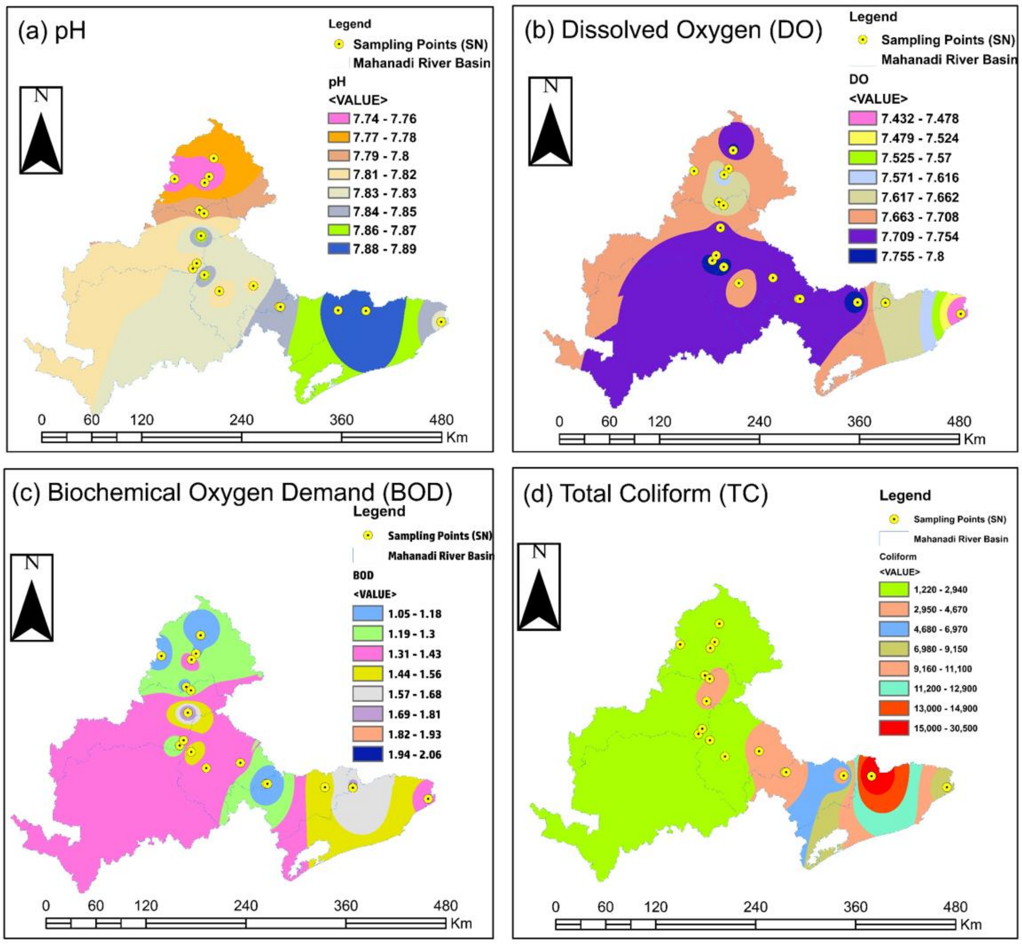
In this study, descriptive statistics are popularly used to detect the trend of variables and the interrelation among variables. It is noteworthy that the World Health Organization (WHO) [37] regulations pertaining to drinking water, are recommended for comparison.

4.1 Spatial and temporal variation of surface water parameters

It has been noted that pH can be used to determine whether surface water seems acidic or alkaline. In addition, the photosynthesis process that algae and aquatic plants use in the river water requires hydrogen, which may possibly be a factor in the water's high pH. In the present work, the value ranged from 7.741-7.913 mg/l, indicating the mild- alkaline state. Most of the locations had pH levels that were under the allowable drinking limit as stated by WHO (6.6-8.5). In addition, a number of factors, such as temperature and pressure, chemical composition, and biological activity, affect the concentration of DO in water [38]. In this work, its value spanned from 7.257 to 7.812 mg/l. Nearly every station, DO, for drinking water, surpasses the acceptable threshold (6.0 mg/l). All aerobic aquatic life, however, depends critically on the DO level in a body of water; higher DO levels will preserve biological variety. When assessing surface and ground water pollution caused by the dumping of household and industrial effluents, the BOD parameter is necessary. Its readings in the current study varied from 1.095 to 2.389 mg/l, which is, according to WHO guidelines, less than 5 mg/l at all sites. This arises because of the dilution of the effluents and the little to no mixing of organic compounds, the BOD level in this river water has decreased [39]. Therefore, in this study, the presence of coliform bacteria guarantees faecal contamination in the water body, indicating a higher risk of illness and an unfitness for drinking. During the study period, the TC count ranged from 1219 to 42530 MPN/100 ml, suggesting all stations are within the prescribed limits (>5000), except for SP-(8), (9), and (19). So, it is advised that the existence of larger coliform colonies at three locations suggest a high level of bacterial contamination, which caused a significant portion of the urban population to contract typhoid and dysentery. Notably, another metric, TSS, provides information on all particles of organic and inorganic debris that float in the water, including silt, clay, and fine particles of other materials. A high score lowers the DO level and lowers the clarity of the water by reducing the quantity of light entering the water and slowing down photosynthesis [40]. The concentration varies from 28.62-74.88 mg/l, in the current investigation. Therefore, the results showed that the reported readings of TSS in the river water were within the desirable limits of 100 mg/l. Meanwhile, at the sampling sites, alkalinity was found to be between 70.398-100.88 mg/l, which is detected between 200 mg/l and higher. Compared to other stations, the water at SP-(9) appears to be somewhat more alkaline, which could be because of the extra salts present. Nonetheless, the findings suggest that acidic pollution from waste water or rainfall could be neutralized by the river. When it comes to COD, it serves as a crucial marker of organic pollution originating from sources like partly or untreated urban domestic and industrial wastewater. When it reaches its stated level in drinking water, it may have a detectable taste, and in certain consumers, it may have a laxative effect at very high concentrations. The value obtained in the current work exhibits a range between 6.75-21.87 mg/l. As [37] prescribes, the highest amount that is allowed is 30 mg/l in case of drinking water. Subsequently, Ammoniacal Nitrogen (NH_3-N) and free ammonia (Free-NH_3) concentration, are generally thought to be the most important surface water contaminant when taking agricultural and drinking usage into account. Since nitrate is linked to the breakdown of organic matter from sewage, household wastes, animal dung, and nitrogen fertilizers, elevated levels of both markers in the research region are primarily indicative of anthropogenic activities. The primary components are livestock, farming-based and commercial wastes [41]. The reported findings of NH_3-N and Free-NH_3 ranged from 0.511-1.928 and 0.021-0.059 mg/l respectively. However, all observations were within the prescribed limits (<2 mg/l) for all sampling locations. It is demonstrated that greater TKN values are linked to areas that are partially or fully irrigated with untreated wastewater, solid waste disposal sites that have higher nitrate values in the research area, and untreated wastewater irrigation areas. Additionally, the primary cause of the contamination of the potable water for human use was the overuse of inorganic fertilizers and plant nutrients. The levels in the current studied region ranged between 3.279-11.791 mg/l. In spite, its readings should not exceed the threshold of 5 mg/l, as per WHO criteria. The results show that the majority of the time, values are higher. This results from the mixing of human and animal wastes, runoff from agricultural land, and anthropogenic contamination. This crucial quantity, EC, indicates the amount of ionized compounds in water and serves as a reliable indicator of salinity [42]. But a low result means there are less ions in the water, which makes it safe to drink; on the other hand, a high EC shows that there is a lot of mineralization in the water because of anthropogenic and geogenic processes. The research area's surface water had EC values ranging from 138.11 to 7779.342 mg/l. The results highlighted that water samples in all the locations were found within the recommended limits of 2250 mg/l according to [37] and can be used for drinking water without any further treatment except at the site i.e., SP-(9). So, this location shows that the activity of geochemical processes vary widely. Therefore, the salinity factor resulting from mineral dissolution clarifies it. Numerous young authors have noted that greater SAR values in drinking water may lower osmotic pressure, which in turn may limit plants' uptake of nutrients from the soil [43]. Furthermore, soil clays inflate and disperse as a result; surface crusting and pore clogging prevent recharge water from penetrating the soil. In the period of the concerned study, the surface water shows a score of 0.412-16.589, which is well within the acceptable limit of 10 mg/l, except at place, SP-(9). Elevated readings at SP-(9) in drinking water, frequently unsuitable for irrigation and drinking, which results in the deterioration of soil qualities that alter the soil's structure and make it alkaline. Higher values might also be associated with the mechanism of cation exchange. Based on the research, it has been calculated that the TDS content is high at SP-(9) & (19). It also highlights that TDS values at each sampling station were within the permissible limit (WHO, 100 mg/l). More TDS is because of heavy precipitation, which could be more than it can transport [44]. These elevated values originate as a result of the river receiving discharges of industrial effluent, agricultural runoff, and household sewage. Likewise, different dissolved polyvalent metallic ions, primarily Ca^{2+} and Mg^{2+}, are the source of water hardness. One of the ions that causes surface water to temporarily become hard is Ca^{2+}, and consuming too much of it through drinking water can be harmful to one's health. Additionally, Mg^{2+} facilitates the correct operation of cells by activating enzymes; however, at greater doses, this can have a laxative effect. It is noticed that the observed TH values vary in the range of 51.18-2194.90. According to WHO [37], the highest permitted limit is taken as 300 mg/l. Its results show that the area is within the TH limit and is safe to drink in, with the exception of SP-(9). Though, SP-(9) was observed to be higher, sometimes, is the result of erosion and mineral formation from carbonate, and its value beyond permissible limits, resulting in boiler and pot scaling as well as renal failure in people [45].

4.2 Ionic Distribution in the Studied Area

The following represents the primary ion concentration in the area: The main ions' order of abundance is considered as $Fe^{2+} > B^{+}$; and $Cl^{-} > SO_4^{2-} > NO_3^{-} > F^{-}$. The indicator such as Iron (Fe^{2+}), serves as a vital trace element that is necessary for optimal health and was obtained from industrial and natural waste water. At higher concentrations, it may induce fatigue even while it facilitates blood oxygen transportation. It also describes how rainwater that came into contact with the soil raised the river's Fe^{2+} content. Also, highly concentrated iron water can become murky and turn reddish brown. In the study period, the iron ranges between 0.59-2.609 mg/l, within the permissible limit of 1 mg/l. Meanwhile, the main causes of B^{+} contamination of surface water were chemical fertilizers, sewage disposal, and residents' waste being dumped in open spaces. Yet, there was not a health concern associated with the level of toxins in the river, and the research region's values at this time, were lower than the WHO standard of 2 mg/l. In the case of Cl^{-}, by neutralizing and oxidizing bacteria, parasites, viruses, and microorganisms, this parameter is utilized in water treatment to eliminate these elements from the water. The permissible limit of Cl^{-} is 250 mg/l as per WHO standards. In the present study, its concentration ranged from 9.648-4904.88, and its readings remained below the maximum allowable level at all sampling locations except at SP-(9). The reason for greater concentration at SP-(9) site is a result of the region's geology, agricultural runoff, industrial effluent, and domestic sources. On the other hand, sulphate (SO_4^{2-}) happens spontaneously in surface water as a result of sedimentary and igneous rock weathering. As air temperature rises, more evaporation occurs, which also contributes to an increase in this parameter value. The amount of sulphate in water rises as a result of household and industrial waste. In this regard, the value was considered to be in the range of 4.97-376.07 mg/l, in the current work. However, the present study observes that the lowest recordedSO_4^{2-} value was observed at SP-(13) and the determined highest score is noticed at SP-9 (376.07 mg/l). Its levels could potentially become unstable if their concentration surpasses the WHO [37] standard level (200 mg/l) and can cause a laxative effect on human health. It is found that an increase in concentration at SP-(9), may be connected to runoff from agricultural, given the research area's high level of activity induced by agriculture. The principal sources of high fluoride (F^{-}) rates in India are the weathering of fundamental rocks and the liquidation of fluoride-containing minerals, which are typically linked to low calcium levels and high bicarbonate ions. At low concentrations, it prevents and minimizes risks that damage teeth, which has a significant impact on teeth. Likewise, it is good for human health to consume water that has a legal level of 1 mg/l. High F^{-} levels are connected to the region's dental fluorosis. The current study's quantification of F^{-} concentration was discovered to be 0.258-1.0 mg/l. After a disinfection procedure, the water could be utilized for drinking at all sites because the concentrations were within the WHO acceptable range. The main cause of nitrate (NO_3^{-}) in surface water is anthropogenic activity and widespread agriculture-related nitrate leaching into the permeate water [46]. Surface washing, phytoplankton absorption, and bacterial nitrate denitrification can all cause its levels to rise quickly, while increases in ground water nitrate levels usually happen gradually. Furthermore, as a result of several agricultural and related activities, such as the excessive use of synthetic nitrogenous fertilizers and manures and the dumping of wastewater by particular enterprises, its concentration level can be seen in both surface water and groundwater [47]. The results in the current region revealed that its readings were in the range of 1.289-2.689 mg/l. In all sites, levels are within the criteria limit of 45 mg/l. From the above analysis, it is seen that two indicators such as TC and TKN exhibit greater values, which exceeds the guidelines suggested by WHO standards, because of different sources of availability of geogenic and anthropogenic origins [48]. Thus, the interpolated maps of different water quality parameters is shown in Figure 3a-t.



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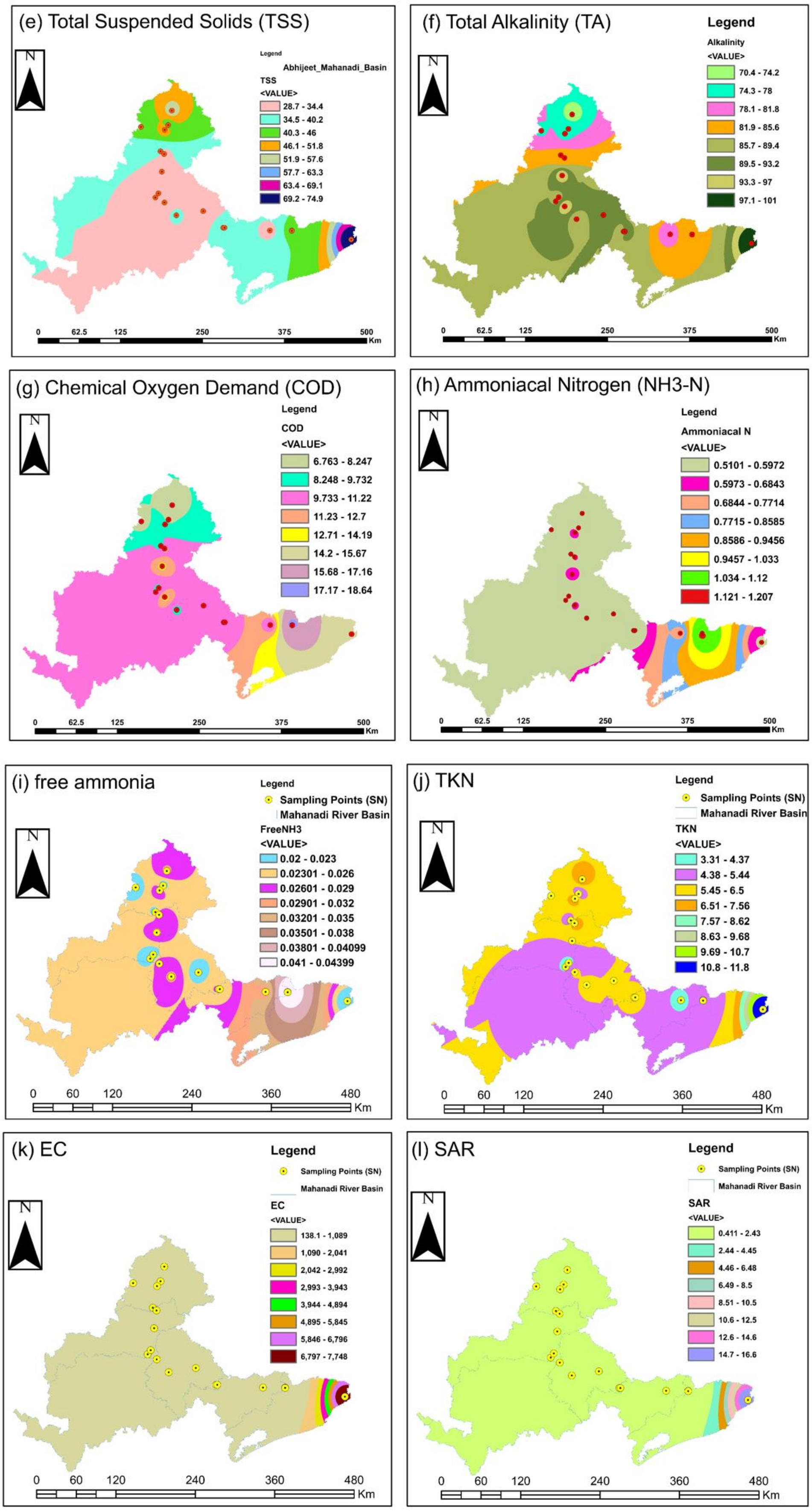


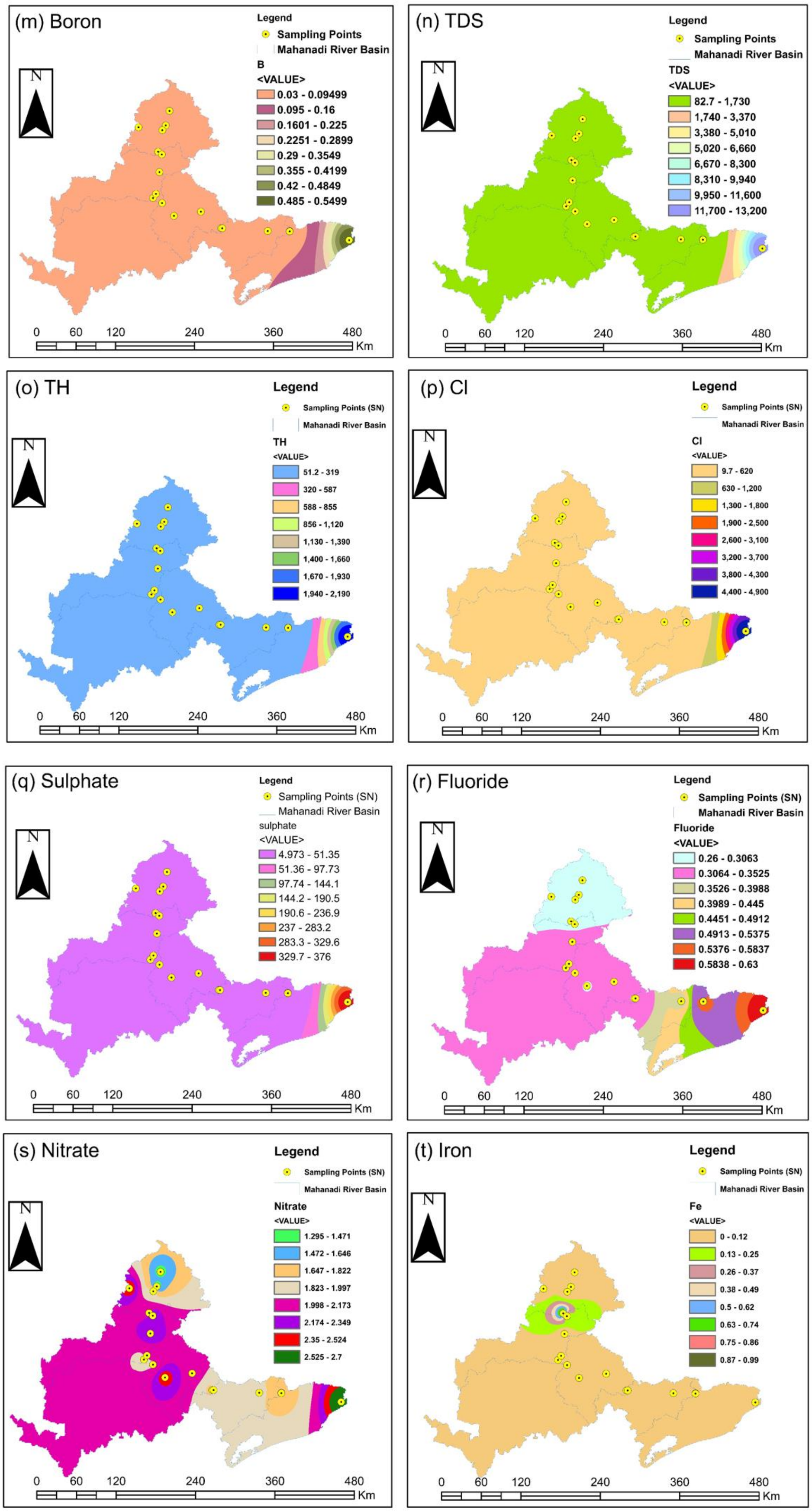


Figure 3 (a-t): A spatial distribution maps of individual physiochemical parameters

4.3 Classification of Surface Water Using Relief Algorithm

With regard to traditional WQ approaches, this leads us to conclude that the problematic status of any surface water body is not indicated by the analysis, monitoring, or index development alone. As a result, the RA-WQI approach makes it simple to identify, during further analysis, the relative pollution levels of the sampling locations in relation to drinking water quality criteria [49]. These RA-WQI values according to the WHO drinking water quality guideline for each sample are displayed in Figure 4 (a & b). The RA-WQI in the current study varied from 15 to 488, which depicts excellent to unsuitable categories. Approximately 15.79% of the sample locations (n=3 each) exhibit excellent and good conditions, 36.84% (n=7) depicts poor, 26.32% of the selected sites (n=5), depicts as poor category of water, and ultimately, 5.26% of tested points (1 location), referred as unsuitable water quality. Also, elevated values exhibited at SP-9 site because of EC, SAR, TDS, TH, Cl^-, SO_4^{2-}, TKN, and TC. In fact, the sequence actually showed that the river's water quality was in excellent condition prior to entering the urbanized area and later declined as a result of the addition of untreated industrial and domestic wastewater, which flowed past the municipal line and on to the downstream sampling site SP-9. But this is unquestionably an example of both organic and inorganic contamination from human sources, including water treatment facilities, untreated municipal sewage discharge, and residential waste water [50]. The developed interpolated map has been illustrated in a GIS diagram displayed in Figure 4c. In addition, the places, namely SP-(2), (8), (9), (10), (11), (12), (13), and (19) showed poor/unsuitable water quality throughout the entire period. Thus, except for these eight stations, most of the study area's surface water quality falls into the excellent or good category, making it fit for both domestic and drinking purposes. Hence, water quality assessment indicates that because of excessive levels of coliform, salinity, nitrogen, and other components, more than 50% of samples are not acceptable or appropriate for drinking. This supports not only nitrification in this area but also the impact of human and natural input on water chemistry. Thus, by taking into account all significant factors and allocating weight based on their variability, it is a scientific method of evaluating the water quality. However, this approach's distinctive method of allocating weight based on the observed data sets makes it usable globally and not only in a given location.

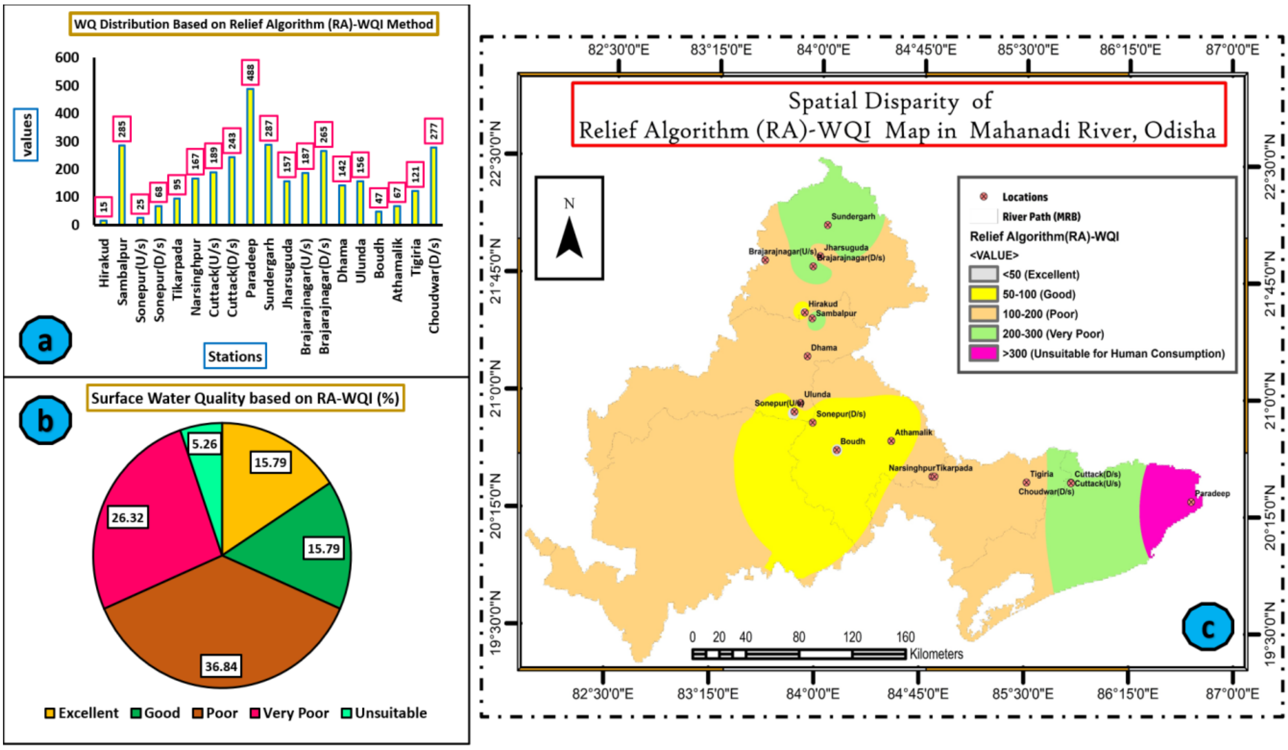
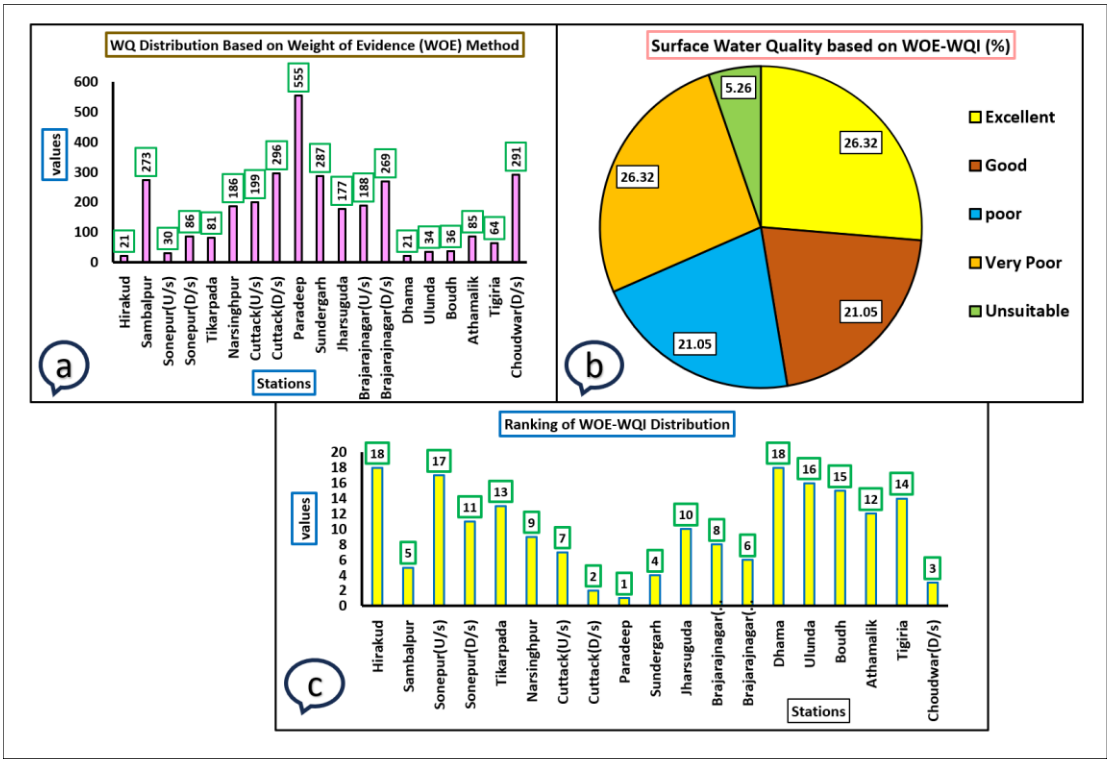


Figure 4. RA-WQI rating of various sampling sites (a) Concentration levels, (b) % of distribution and (c) spatial interpolation map by IDW

4.4. Suitability of Surface Water Using Weight of Evidence (WOE) Approach

Consequently, another mechanism of decision-making, namely, WOE, is suggested to use the following formulas covered in the methodology to compare their rating processes and averaged rating. However, the MCDM calculation's impact on the RA-WQI ranking may grow if each parameter's normalized value is used. Thus, these sites were likewise classified as the most polluted by the WOE approach, which also determines the relative pollution level at each place and assigns an overall score to them within the selected region. Its WQ score, ranking, and its % of distribution of all the sampling locations are shown in Figure 5 (a-c). The result was significant and regarding spatial location, the reported value varied in the range between 21-555. Considering this, the outcomes in the studied region, observed that the location SP-(8) holds a score of 296 and site-(19) also holds a coefficient of 291, which possesses the second and third highest RA-WQI indicating it as poor water class. It is observed that DO is negatively loaded with coliform along the river, as due to low population density, absence of large industries and limited urbanization in the catchment area. A major part of the catchment area is rural in character with agriculture and allied activities being the main occupation of the population along the river. In addition, a place like SP-9 (555) is situated in the zone of heavily polluted location, with an overall rank of 1, on account of higher concentrations in eight parameters namely, EC, SAR, TDS, TH, Cl^-, SO_4^{2-}, TKN and TC, which were also higher than their desirable concentration and highest among all the locations. A higher value in four places namely, SP-(9), (8), (19) and (2) is noted, that follows the trend of higher TKN and TC. As was already said, farming is a common activity in this research area, and different fertilizers are frequently used. Additionally, past discussion makes a solid case for the geogenic origins of TKN and coliform. Similarly, TH and Cl^- have a strong correlation. This can be attributed to a number of factors, including nitrification, wastewater from surface and subsurface pollution sources, and irrigation return flow. SAR also drastically restricts crop choice and negatively impacts crop germination and output. The physical properties of soil break down when there is an increased concentration of Na^+ in the water. As a result, it changes the soil's physical state and texture, making it difficult to plough. Moreover, EC describes how mineral weathering functions in the research region. Thus, it is also demonstrated that there is no meaningful relationship between pH and any other riverine physical or chemical characteristic. This demonstrates unequivocally that there are no fixed elements that can control the source of pollution in the river. Regarding the lengthy discussion above, the total results show that "poor and unsuitable locations" indicate the presence of high levels of pollutants from sewage disposal, agricultural runoffs, textile industry, and related industrial effluents. They also show that these areas cannot be used for drinking without treatment. Finally, the extracted results in Figure 5d, were then contoured to identify areas with good and bad water quality using geostatistical approaches.



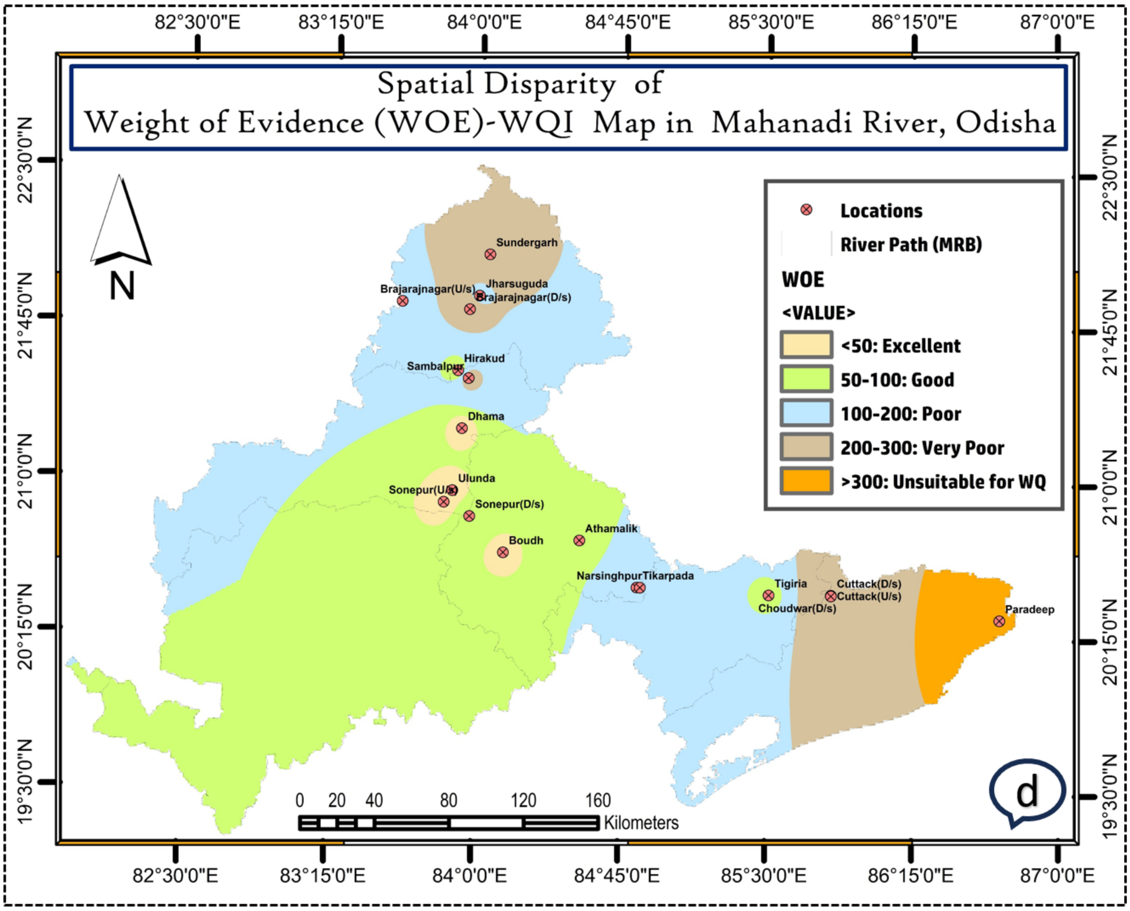


Figure 5. WOE-WQI rating of various sampling sites (a) Concentration levels, (b) % of distribution, (c) Ranking score and (d) spatial interpolation map by IDW

5. Conclusion and Recommendations

The purpose of the current study was to determine surface water quality of Mahanadi Basin, Odisha, in order to understand the suitability for human consumption, considering 20 water quality (WQ) parameters collected yearly from nineteen water sources. The time frame taken into consideration is 5 years (2018-2023). The integrated-based RA water quality index (WQI) and ML technique such as WOE method, were used in order to calculate the outcomes. The RA-WQI should be used very carefully since it creates a misleading impression of the cleanliness of the water by hiding pollutants at levels that are higher than what is considered acceptable for drinking water. The results in the study area, confirm that the majority of the assessed indicators fell within the WHO's permissible range, except the possible exception of 2 indicators namely, TC and TKN. Additionally, the river water is slightly alkaline and DO is quite healthy. The results show that the trends for anions and cations are different and illustrated as: $Fe^{2+} > B^{+}$ and $Cl^{-} > SO_4^{2-} > NO_3^{-} > F^{-}$ respectively, during the taken period. According to the RA-WQI, it is seen that around 31.57% samples are found to be fit for drinking, where the values lie in the range between 15 and 488. However, its findings reveal that 6 samples are termed to be of excellent-good water quality in terms of drinking and around 13 sample is seen to be poor-unsuitable for drinking purposes. This could be ascribed to the sites that are located at the periphery of industrial area and it is mainly influenced by excessive concentrations of many parameters and, due to the impact of industrial and intense human activities. However, a reliable atmospheric adjustment plan and efficient water quality parameter estimation methods, were employed in this work to reduce the RA model's errors, which are brought on by miscalculations and uncertainty regarding the products derived from satellites. This led to increased dependability and accuracy in water quality assessments. So, the appropriateness of surface water for drinking operations was calculated with the developed WOE model, which on applying on the dataset, generates a value in a range of 21-555, signify excellent to unsuitable category of water and further ranked the site i.e., SP-9 (555) as the most contaminated sampling point on the degree of performance score or closeness coefficients, followed by 2nd i.e., SP-8 (296) and 3rd i.e., SP-19 (291). This was carried out as a component of the water quality assessment for safe drinking water. Sewage infiltration and synthetic fertilizers are the primary sources in the examined area. However, as evidenced by the preponderance of carbonate rock in the aquifer material, water-rock interaction is the main natural process influencing surface water quality. The nitrogen and coliform levels in the river's water also pose a serious risk to human consumption. With a few exceptions, all surface water samples that were analysed were of a quality that made them safe to drink. There was also no seasonal variation in the chemistry of the surface water. The results illuminate the preservation and distribution of drinkable and irrigable surface water supplies, and provide decision-makers with a valuable resource for implementing successful surface water protection strategies in the area under study. It is strongly advised that this study contribute to the understanding of surface water quality and status temporal and spatial variations for various users, including agricultural users and consuming purposes. It is anticipated that best management practices and effective land use planning, including enhanced agricultural and sanitation methods, will be used in this situation. Additionally, by utilizing past data on water quality as well as other environmental elements, combining the study with soft-computing techniques can result in the creation of a predictive model that will improve accuracy, dependability, and the capacity to anticipate future changes in water quality.

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Author contributions

All authors contributed to the present study through data collection, material preparation, analysis, and core findings. Abhijeet Das prepared methodology, Data collection and analysis, core findings and conclusions, writing review-editing, and supervision.

Declaration of Competing Interest

The author declare no conflict of interest/ competing interests

Data Availability

Data will be made available on request.

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