Assessing Surface Water Quality for Drinking Water Supply using Hybrid GIS-Based Water Quality Index (WQI) in Mahanadi River Basin (MRB), Odisha, India

Abhijeet Das

Research Scholar, Department of Civil Engineering, C.V. Raman Global University (C.G.U), Bhubaneswar, Odisha, India

*Corresponding author's e-mail: das.abhijeetlaltu1999@gmail.com

doi: https://doi.org/10.21467/proceedings.160.1

ABSTRACT

Surface water is an important source for drinking water supply in Mahanadi Basin, Odisha. The research was done to evaluate the water quality, that serves as the source of domestic water supply to many cities. Samples of water were taken from nineteen important sampling areas for a period of 2010-2023 and twenty water quality parameters were examined to determine the WQI, followed by Multi-Criteria Decision-Making (MCDM) evaluation. Employing the Weighted Arithmetic (WA) Water Quality Index (WQI) and Stepwise Weight Assessment Ratio Analysis (SWARA) WQI, this study finds areas where cumulative variables, such as sewage discharge, a falling water table, dilution, and surface runoff, that tends to cause water quality variations in a water body, over a given monitoring period, have had the greatest impact. The WA WQI and SWARA WQI in the study area ranges from 23.78 to 96.09 and 14.6 to 1065.2, respectively. Also, the river water ranged from excellent to very poor,encompassing excellent for approximately 15.8%, good for 68.4%, poor for 10.5% and very poor for 5.3% in case of WA WQI. While the general water quality, as per SWARA-WQI, it varied from excellent to extremely poor, comprising 84.21% excellent, 10.53% poor and 5.26% for extremely poor category. The overall WQI in the study area indicates that the surface water is safe and potable except few localized pockets in SP-(8), (9) and (19) blocks. The cause could be attributedto anthropogenic sources such as domestic sewage and agricultural runoff altered a few parameters– e.g., TKN and TC. Based on geostatistical results, Gaussian model produce a more accurate assessment as per nugget/sill ratio, ASE and RMSE. To delineate the feasible regions for drinking practices, MCDM models such as Compromise Programming (CP), Ordered Weighted Averaging (OWA), and Combined Compromise Solution (CoCoSo), were adopted. Finally, the results demonstrated that WQI generated using both indexing strategies matched the outcomes of MCDM models. To sum up, it is advantageous and gives a clear image of water quality to combine physicochemical properties, WQIs, MCDM, and GIS technologies to evaluate surface water suitability for drinking and their controlling variables.

Keywords: Mahanadi Basin, SWARA, OWA, CP, CoCoSo

1 Introduction

With a rise in global population, the quantity and quality of water, a necessary but limited resource, are declining (Naseem *et al.*, 2021). Many human cities and ancient civilizations were supported by rivers as a vital source of fresh water, allowing them to flourish in their catchments (Cho *et al.*, 2021). But quick, unexpected, and uncontrolled changes to the physical terrain can cause water resources to degrade and become scarce (Varol 2020; Weibe 2021). One of the world's most vital water resources is surface water, which is used foressential purposes like drinking, agriculture, and industry (Park *et al.*, 2020). In general, agricultural and industry development were primarily influenced by population increase and the expansion of urbanization, which led to water instability difficulties (Moussa *et al.*, 2020). Negative effects such as soil contamination, water pollution, and contamination of agricultural goods will result from the discharge of

Proceedings DOI: 10.21467/proceedings.160; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-965621-9-9

untreated or only partially treated wastewater and its reuse in agricultural farms as irrigation methods (Silvestri *et al.*, 2021). It is necessary to combine a number of characteristics into a single composite value in order to simplify this challenging operation and provide ascientifically sound summary of water quality (Das, A 2022; Holocomb and Stewart 2020).There are, however, not many research, that describe how surface water irrigation and drinking affect the entire water cycle, from consumption to water to soil to crops. Consequently, there is a pressing need to create effective management plans for the sustainable use and preservation of essential surface water resources (Zhang *et al.*, 2020a). To fill in this gap, earlier researchers have designed the framework of Water Quality Index (WQI). As a result, WQIs may be evaluated using a straightforward mathematical process that reduces a vast array of water attributes to a solo quantity thatrepresents the sum of all water quality characteristics (Nong *et al.*, 2020). In order to distinguish between different types ofwater quality, Horton created the WQI model in 1965 (Horton 1965). It is an easy and reliable method for figuring out the quality of the water. Since then, numerous indices have beenput out, but there is no WQI that is universally recognized (Gao *et al.*, 2020). Several academics (Jampani *et al.,* 2020) created a number of WQI structures, designed on the evaluation and weighting of various water quality criteria, which gets inferred using weighted arithmetic (WA) strategy.When employed in this context, metrics are frequently equalized or weighted, according to their perceived importance, to overall water quality (Islam *et al.*, 2020). It is crucial to weight the characteristics based on how much wateris used for drinking, domestic usage, or irrigation because excessively weighted parameters have the potential to negatively impact the index's sensitivity (Bui *et al.*, 2020). Byproperly assigning weights, issues like eclipsing and ambiguity can be resolved (Jia *et al.*, 2020). To overcome the erroneous parameter weighting and to get rid of the subjective weighting assigned by prior approaches (Singh *et al.*, 2020), the Stepwise Weight Assessment Ratio Analysis (SWARA) was proposed by Zolfani *et al.*, (2013) that caught the parameters' built-in unpredictability. The precision and objectivity of SWARA weights are higher and stronger compared to those subjective appraisal methods, which can more fully explain the outcomes obtained (Kersuliene *et al.*, 2011). In the past few years, the use of analytical tools to handle issues with water resources has considerably risen, and multi-criteria decision-making (MCDM) processes are now widely recognized as being particularly effective at solving issues with water management (Dash and Kalamdhad 2021; Gupta 2022; Rashidi 2022). In the current study, three alternative MCDM approaches such as Ordered Weighted Averaging (OWA), Compromise Programming (CP), and Combined Compromise Solution (CoCoSo), were used to discuss the effectiveness of the WQI index. OWA uses a preference matrix to compare each of the discovered relevantcriteria to one another in order to determine the necessary weighting factors. Reproducible preference factors are used to accomplish this, and they then combine the weights of thecriterion map layers (Yager 1988; Yari and Chaji 2012). However, said that CP would improve water quality rankings and could be used to lessen inconsistencies between the homeand agricultural sectors (Zeleny, 1973). Also mentioned is the CoCoSo hybrid technique, which combines an exponentiallyweighted product model with basic additive weighting. It might lead to a trustworthy study for the weight sensitivity ofseveral physicochemical parameters (Mishra and Rani, 2021).However, CoCoSo is applied to rank the options and choose the safest alternative, whereas SWARA is used to determinethe criteria weight. As a result, these techniques can be used as an effective multi-objective optimization tool to address parametric optimization concerns related to water quality. Tocreate a map that is simple to comprehend and help combine spatial data with other information, Geographic Information System (GIS) based maps are one potential management option. IDW (Inverted Distance Weighting) is an algorithm for calculating values between measurements or spatially interpolating data (Anand *et al.,* 2020). When compared to IDW, the spline and kriging procedures are less advantageous since, respectively, kriging requires more user input and spline demands a great deal more processing and modelling time

Proceedings DOI: 10.21467/proceedings.160
ISBN: 978-81-965621-9-9

Series: AIJR Proceedings
ISSN: 2582-3922

(Karuppannan and Serre Kawo 2020). However, using WQI and MCDM in conjunction with GIS to appraise the acceptability of surface water for human consumption, is a fantastic technique to portray water quality (WQ) and identify the causes of quality decline. In order to determine how population, increase, urbanization, and industry have affected the water body, it is crucial to monitor the efficacy of surface water in the Mahanadi basin and its surrounding areas. Till date, less thorough research projects have been conducted onboth sides of the river, to ascertain the primary pollutant sources and their effects on surface water. To evaluate the WQ of this region, not even a single study has combined the application of WA, SWARA, and MCDMs such as OWA, CP, and CoCoSo. As a result, there is a study gap in this area, and more discussion is required to understand the scope and factors of WQ deterioration. In light of the aforementioned backdrop, this ongoing region has been selected in order to conduct a thorough analysis utilizing combined GIS and MCDM methodologies. Hence, this document will be useful for determining the overall circumstances of the river's quality and for assessing pollution and developing sustainable solutions.

2 Study Area

The study region is a segment of the Mahanadi River basin (MRB), which covers an area of about 141,600 Km^2 and is considered to be the third largest in the Indian Peninsula. It has a long history of providing irrigation for agricultural purposes and fisheries to the Indian states of Chhattisgarh and Odisha (Bastia *et al.* 2020).

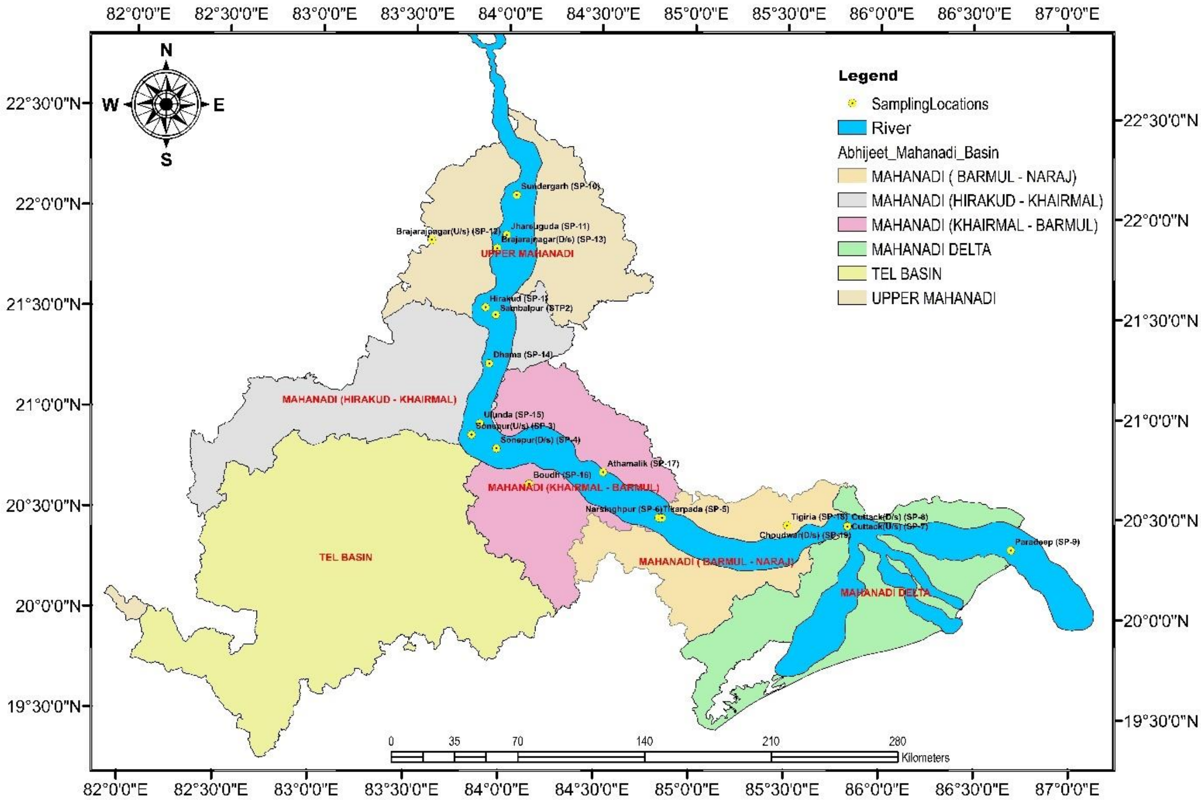


Figure 1: *Location map of the study area (Mahanadi Watershed, Odisha)*

It is also regarded as the longest river in the state of Odisha, spreading over 494 km and flowing across 65,628 km^2 of land. It provides household water to several cities around the state (Panda *et al.* 2020a). The location is determined by geographic coordinates 80°30' E to 86°50'E and 19°20'N to 23°35'N. The basin has a tropical climate with 1200 to 1400 mm of annual precipitation on average. Approximately 54% of the MRB is covered by agricultural land (Das, A 2023). The basin's typical temperature fluctuates between 24°C to 27°C, exhibiting the lowest temperature, highly fluctuating between 10°C to 13°C in winter (Paital & Das, 2021). It has been confirmed that the basin is separated into the Upper (21.34%), Middle (37.16%),and Lower Mahanadi sub-basins (41.5%). Since MRB provides drinking water for a sizable population, precautionsmust be taken to preserve the Mahanadi River's physical, biological, and chemical composition. ArcGIS version 10.5 was utilized to make a map of the study region (Figure 1).

3 Sample Collection

To account for the worst-case scenario of pollution, samplingwas done on an average yearly basis between 2012 and 2023.The Global Positioning System (GPS) captured the coordinates of the 19 monitoring locations. 500 cc of water samples were taken at a depth of less than 30 cm, and they were transferred right away to the field laboratory in the darkat room temperature (Rath *et al.* 2021). Samples were taken from each sampling event between the hours of 6:00 and 9:00AM. These river water samples were taken from the middle of the stream, about two feet below the surface (Uddin *et al.* 2021). The bottles were sealed, labelled, and delivered to the State Pollution Control Board's laboratory in Odisha, where they were kept at 4°C until additional examination. The research area took into account a total of 20 parameters, including, Alkalinity, TKN (Total Kjeldahl Nitrogen), EC (Electrical Conductivity), pH, TC (Total Coliform), TSS (Total Suspended Solids), COD (Chemical Oxygen Demand), NH_3-N (Ammoniacal Nitrogen), DO (Dissolved Oxygen), BOD (Biochemical Oxygen Demand), free NH_3 (Free-Ammonia), SAR (Sodium Adsorption Ratio), Chloride (Cl^-), Sulphate (SO_4^{2-}), Fluoride (F^-), Boron (B^+), Total Dissolved Solids (TDS), Total Hardness (TH), Nitrate (NO_3^-) and finally, Iron (Fe^{2+}). The study for all the parameters used was conducted in accordance withthe analytical techniques of the Standards Procedures for the Examination of Water and Wastewaters, 20th Edition, documented by APHA (2005). The analysis was examined utilizing international standards ION 915 and ION 96.4 as part of the quality control and quality assurance protocol (Das, A 2024). The elements under analysis have relative standard deviation (RSD) values of <=2 %. All of the analytical data' ionic balance errors fell below the permitted range of ±5%, demonstrating the accuracy of the findings (Zhang *et al.* 2020a).

4 Methodology

WQI is a single arithmetic value that represents overall WQ and is based on a weighted average of specified characteristics (Hussen *et al.* 2018). Using the chosen physicochemical characteristics, WA WQI is often used to evaluate the water'squality for consumption. According to Brown *et al.*, (1970) and Shankar and Kawo (2019), the quantitative evaluation of WQ, utilizing the WA WQI, has been conducted, and it is further categorized into five classes. The weight that is assigned to each of the chosen parameters is subjective and up for debate. In order to calculate SWARA-WQI, each parameter is given a weight based on SWARA. It is an improvement over the currently used conventional WQIs. Init, professionals employ their own implicit knowledge, experiences, and knowledge, as developed by Kersuliene *et al.*, (2011). Additionally, this strategy has very good accuracy (Omer, 2019). The main benefit is that it produces accurate results because human intervention in the parameter weighting process is completely eliminated. The computational stages, including the definition and ranking of the decision criteria, estimationof each criterion's coefficient, determination of the revised weight, and calculation of the relative weight (W_i), are suggested by (Alimardani *et al.*, 2013). Ultimately, the combination of weights and a rating scale based on quality, which is denoted as Y_i, that results in creating the framework i.e., SWARA WQI = $\sum W_i * Y_i$, where Y_i explains about each variable, which is represented as the proportion of the observed score of the i^{th} indicator (I_i) to its drinking standardlimit (S_i): $Y_i = (I_i/S_i) *100$. The entire methodology and procedures of this investigation are presented in Figure 2 in a flow chart format. For ordering the options, CP and

OWA serves as an MCDM. After normalizing the acquired data, these algorithms may produce accurate ratings of survey sites. By normalizing each qualitative component in these two ways, the positive attribute was elevated in order to observe the effects of individual parameters in addition to theoverall influence on

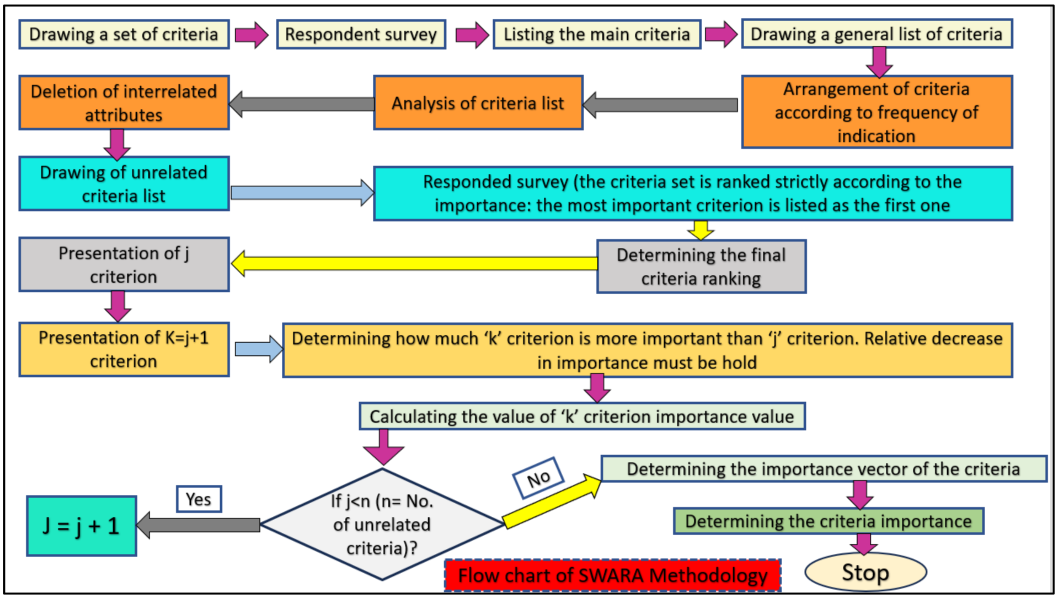


Figure 2: *A Schematic diagram of SWARA methodology adopted in this study*

location ratings (Drasovena and Murariu, 2021). Furthermore, the OWAapproach, which was developed by (Madani and Lund 2011; Das, A, 2023), is a kind of combined multi-criteria technique that evaluates the relevance of each component depending on its particular place as well as its significance across all locations.

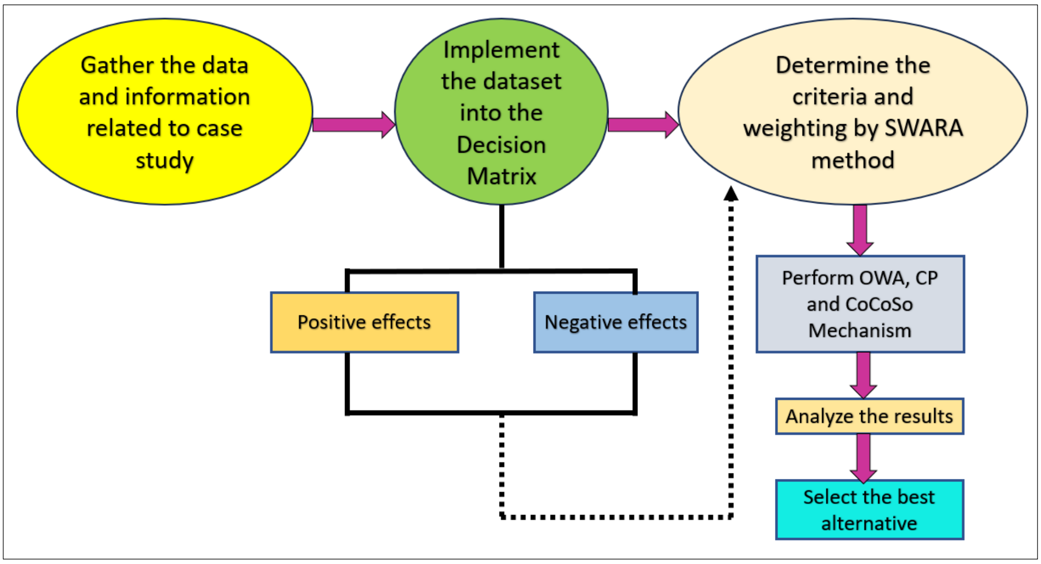


Figure 3: *A Schematic diagram of MCDM methodology adopted in this study*

This method was used to calculate and combine different factors, weights, and constraint maps (Laltu, A. D, 2023). However, CoCoSo is a recently created multi-criteria decision-making (MCDM) technique that generates a compromise solution based on straightforward additive weighting and weighted product models. Its steps are listed as advised by the procedure's (Yazdani *et al.* 2019). This method calculates the composite performance scores of the experimental runs by averaging the power of weighted and sum of weighted comparability sequences. The challenge is based on (Mishra and Rani, 2021), in which the CoCoSo mechanism to be employed to select the best option and construct a ranking order of selection of the numerous possibilities. SWARA analysis is used to evaluate the weight of the criterion. Further, Figure 3 illustrates the interpretation of WQ using MCDM format. Therefore, the main goal of this continuing project was to establish a straightforward WQI calculation process based on MCDM techniques with less effort and greater accuracy for determining the surface and subsurface water quality (Islam *et al.*, 2020).

5 Results and Discussions

In order to compare, the World Health Organization's (WHO) 2011 drinking water recommendations are used. Through the usage of surface water for irrigation and drinking, they are utilized to evaluate the effects of specific chemical parameters on agricultural output and human health (de Souza *et al.*, 2020). The pH of water, which is neutral, indicates the amount of hydrogen ions present (Angello *et al.*, 2020). It stands for the basic or acidic properties of water. The pH value for our investigation ranges from 7.74-7.92 signifying the slightly alkaline nature. The majority of the sites had pH levels that were within the recommended drinking limit as specified by WHO (6.6-8.5). DO helps to evaluate the quality and natural contamination in the surface water. For this study, the DO was noticed as 7.26-7.83 mg/l. For drinking water, the minimum DO allow is 5 mg/l. However, it has been noticed that recorded values were significantly high from all the stations throughout the study period. BOD measures the amount of biodegradable organic matter in garbage and is used to monitor changes in the leachate's biodegradability (Muthusamy *et al.*, 2022). Thecontribution of values was found in the range of 1.05-2.40 mg/l respectively. It is observed that the value was within the WHO standard limit (5 mg/l). The diversity of aquatic organisms may have diminished as a result of the increase in coliform, which indicates that the aquatic ecosystem's balance is upset (Karuppannan *et al.*, 2022). In the ongoing research, the readings fluctuate between 1212-42529 MPN/100ml. Higher levels have been reported in the waters at SP-(8), (9) and (19), which are near to factories, municipal sewers, or hospitals. Afterwards, TSS value ranged from (28.6-74.9 mg/l) which is inside the threshold value of 100 mg/l. It has an impact on aquatic life. Clay and silts, as well as biological solids like bacteria and algae cells, were the main sources of TSS. Higher alkalinity in water, and vice versa, increases its ability to neutralize acids (Das, A, 2023). It should not be higher than 200 mg/l. Alkalinity at sampling sites was discovered to be between 70.4 and 100.90 mg/l. Because of the increased presence of these salts, the water at SP-(9) was considerably more alkaline than water at other locations.

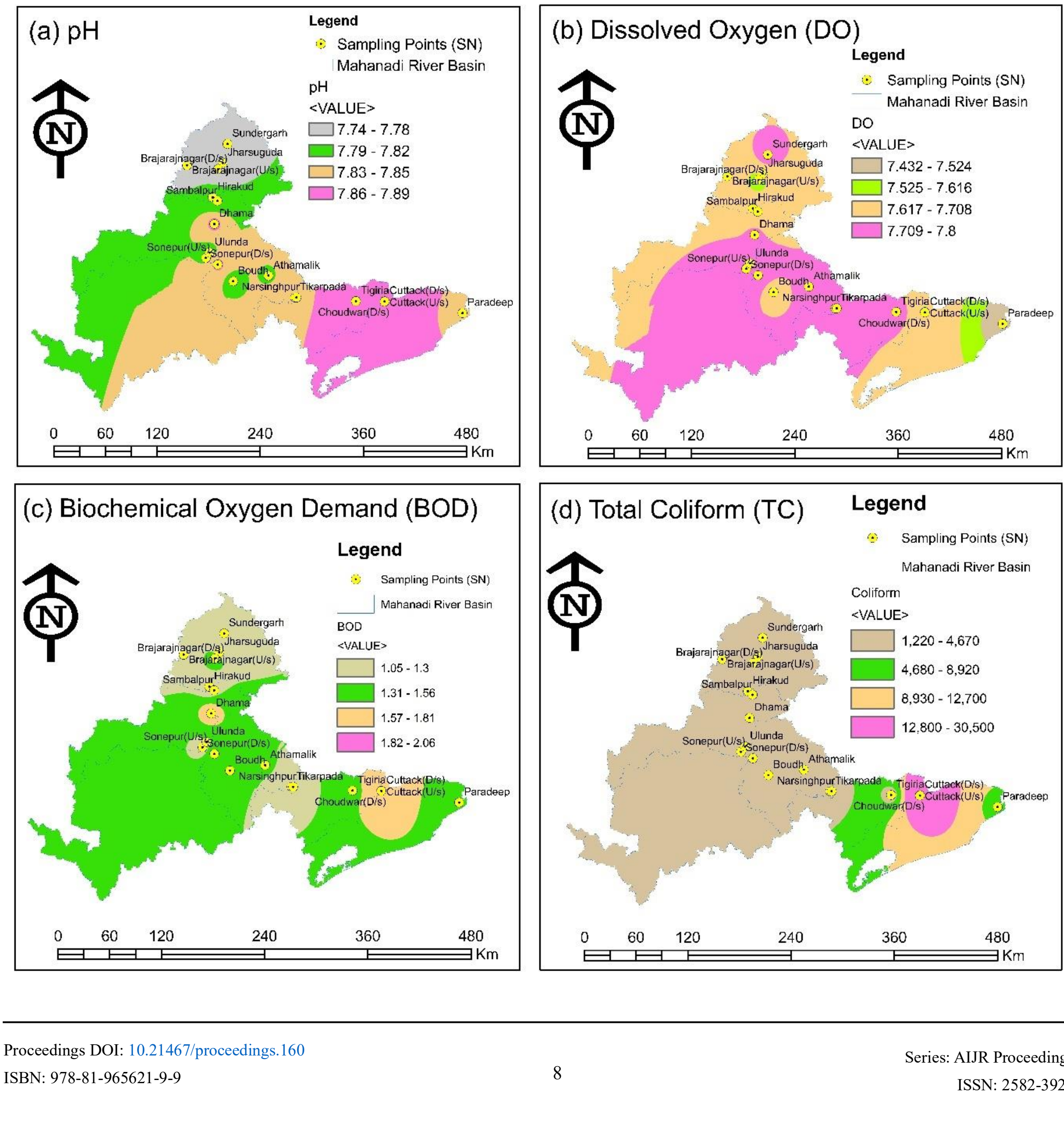
COD is a measure of organic pollution coming from sources like home and industrial wastewater that hasn't been fully or properly treated in metropolitan regions (Haji *et al.*, 2021a; Das, A, 2023). The value in the study area ranged between 6.7-21.88 mg/l, which satisfy the WHO criteria of 30 mg/l. Residents' waste disposal in open areas, excretion of sewage, and chemical fertilizers were the main contributing factors causing NH_4-N and free-NH_3 contamination of surface water. It also results from a broken nitrogen cycle, which releases more ammonia into drinking water, causes eutrophication in lakes and rivers, and worsens the environment and human health. The NH_4-N value recorded as 0.5-1.93 mg/l, well satisfying underneath the WHO guidelines of 2 mg/l. The reported scores of free NH_3 at the respective survey stations were in the range of 0.02- 0.06 mg/l. Threshold limit is taken as 2 mg/l. TKN can result from anthropogenic and natural activities that take place in the surface water environment. If human activity does not change the natural environment, the natural background levels should not go above 5 mg/l. Its levels were discovered to be between 3.28 to 11.80 mg/l. Water quality at SP-(8) and (9) i.e., higher TKN values, reported that the study area exhibits improved agricultural methods, and the primary economic driver for the community is agriculture. The most crucial metric for estimating total ionic concentration is EC, and a high EC value corresponds to a high TDS. It is noteworthy that 2250 μS/cm is the optimum threshold for EC in case of drinking water. Observed value of EC was found to be 138.10.44-7779.35 μS/cm. At SP-9, it is seen that presence of excess salt added in the water, that increases the soil solution's salinity and prevents the crops

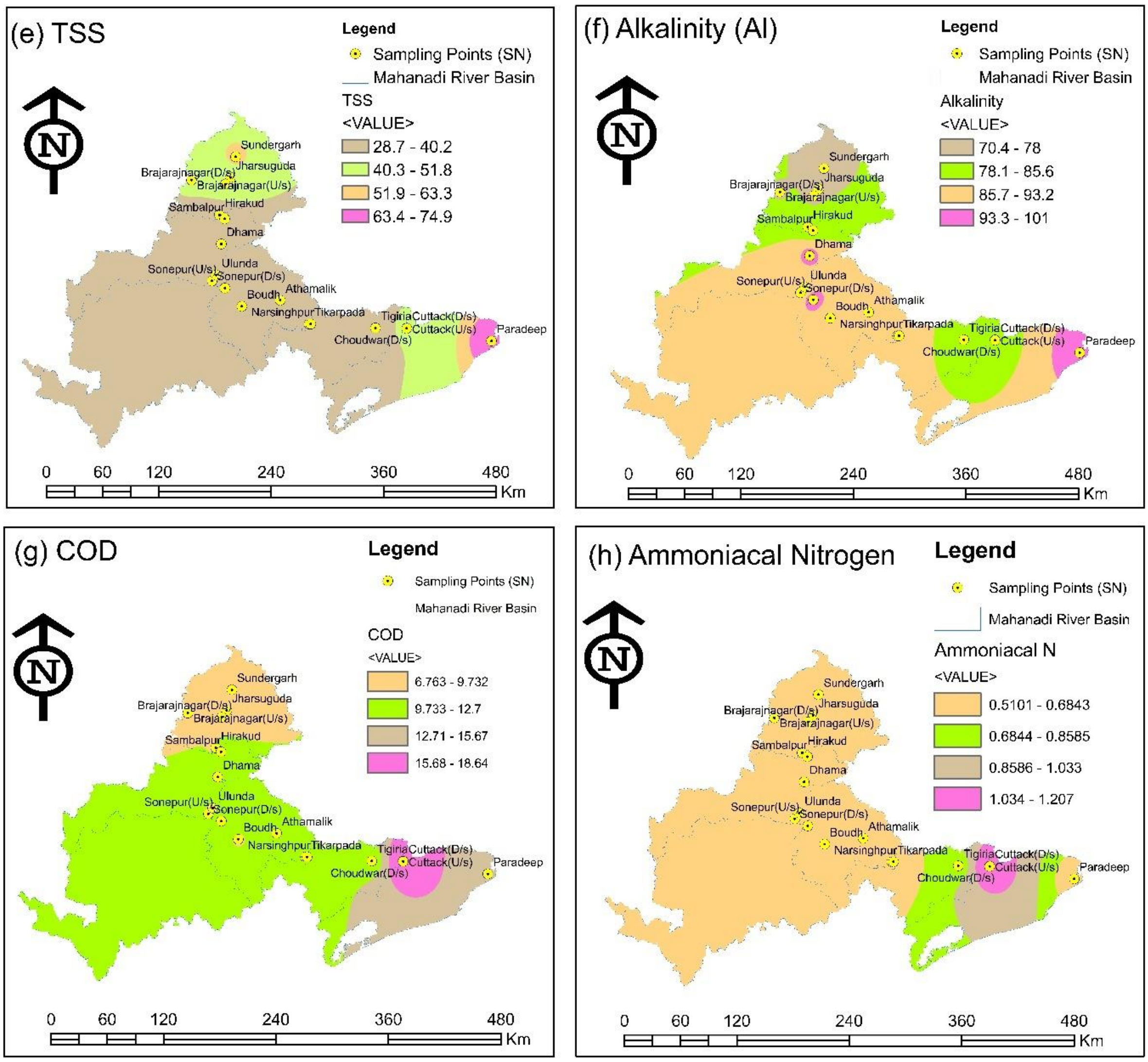
Proceedings DOI: 10.21467/proceedings.160
ISBN: 978-81-965621-9-9

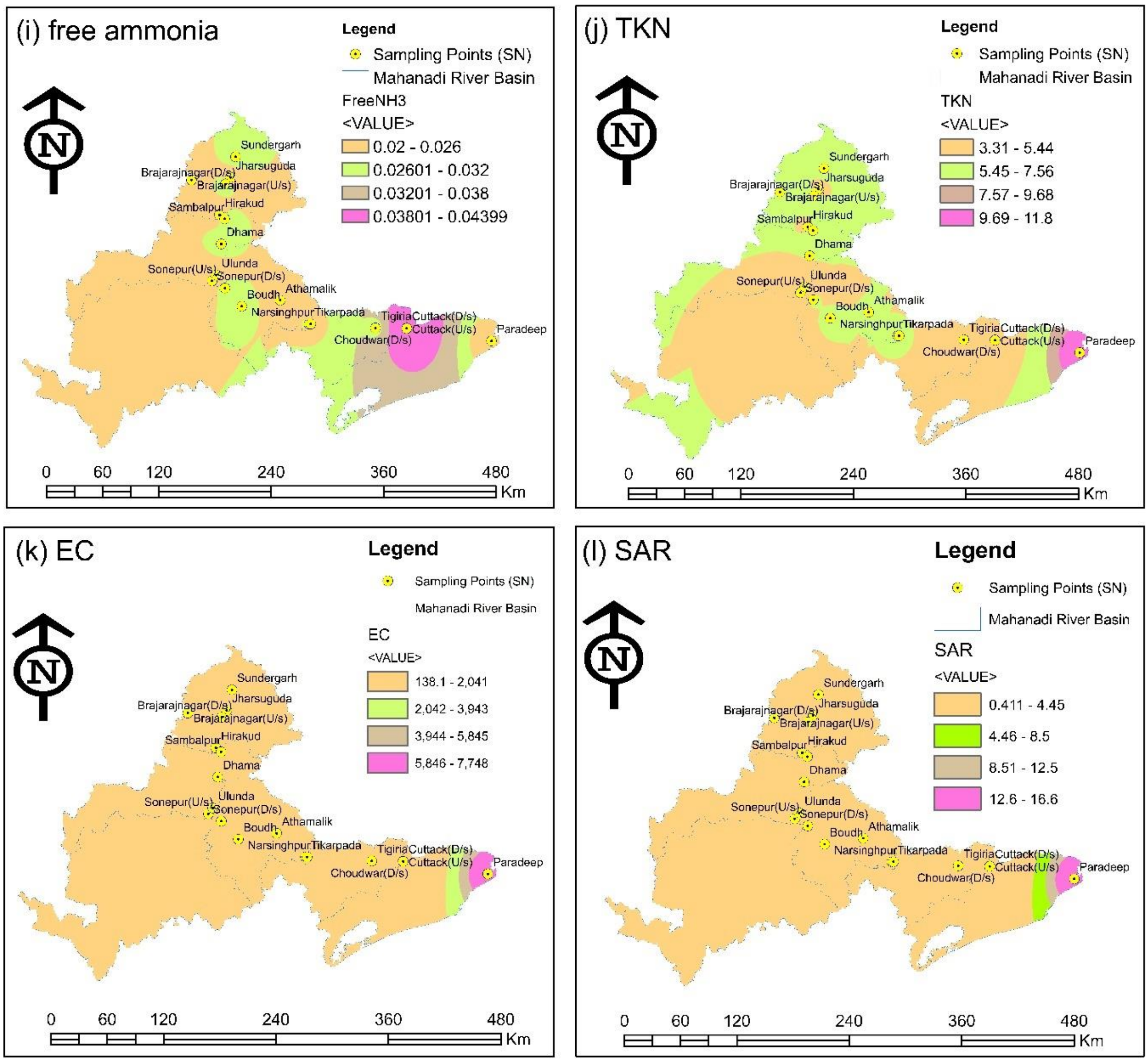
Series: AIJR Proceedings
ISSN: 2582-3922

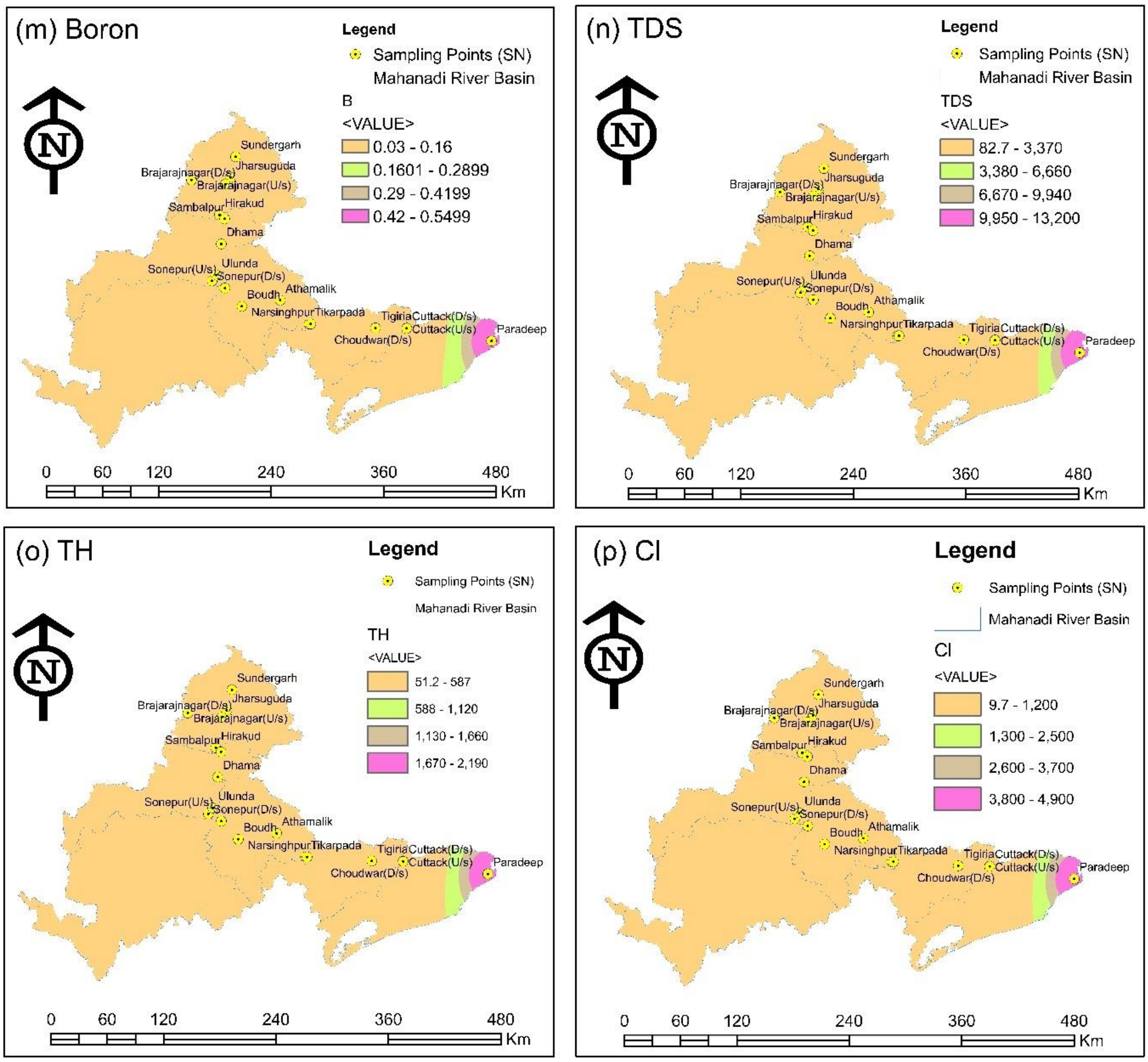
from maintaining the adequate osmotic equilibrium. Crops will wilt as a result of this phenomenon. It might also be attributable to the research area's geochemical conditions and anthropogenic activity. A certain amount of salt is crucial for maintaining good health, but consuming more than the maximum permissible quantity can lead to negative health effects like hypertension and nausea. SAR is therefore the most crucial nutritional component. In the ongoing work, its value lies in between 0.41-16.59 mg/l. The overdose of this indication, however, was felt at SP-9 (SAR> 10 according to WHO criteria), which could increase the danger of nauseousness, vomiting, convulsions, rigidity and twitching of the muscles, as well as cerebral and pulmonary oedema. Boron is a necessary element for plant growth in low amounts, but at higher concentrations, it becomes harmful. Concentration of Boron ranged between 0.03-0.55 mg/l, indicating its appropriateness for irrigation and domestic. With the exception of locations i.e., SP-(19) and (9), all sampling stations' TDS readings (82–13230 mg/l) fell below the permitted range (100 mg/l, according to the WHO). TDS readings that are relatively higher indicate that sewage from homes, runoff from farms, and industrial effluent have been discharged intorivers. High TDS, on the other hand, denotes highly mineralized water. TH is connected to runoff and natural rock weathering (Das, A 2023). If water hardness is too high, it can lead to human renal failure, scaling in pots and boilers, and other problems (Sunkari *et al.*, 2020; Das, A, 2023). In the investigated region, readings varied from 51-2195 mg/l were reported. Except for SP-(9), all specimens were included inside the permitted level (300 mg/l) for drinking. Beyond this Limit, the taste of water becomes more abrasive. Cl- is a chemical that is used in watertreatment to kill bacteria, parasites, viruses, and microorganisms by neutralizing and oxidizing them. Most often, natural sources, sewage and industrial effluents, fertilizers, leachate, and saline intrusion are where Cl^- in drinking water comes from. Cl^- value was observed to range from 9.65 to 4904.91 mg/l. The permissible level set by the WHO is 250 mg/l. When Cl^- is present in excess at SP-(9), it makes water taste salty, increases its corrosivity, and can have a laxative impact on people. Given that there is significant agriculture-related activity in the research area, the rise in sulphate content may be related to runoff (Gebere *et al.* 2021). High $SO_4{}^{2-}$ concentration causes gastrointestinaldiscomfort in people and has a purgative impact. With the exception of SP-(9), the range in the current study is 4.97– 376.07 mg/l, which is substantially within the 250 mg/l acceptable limits. Significant quantities at SP-(9) may also be caused by anthropogenic activity like industrial pollution. Due to geological processes, F- is primarily found in water (Panneerselvam *et al.*, 2021). The value of F^- was discovered to range from 0.26 to 1.00 mg/l. The WHO recommended limit was met at all sites, the concentration of F^- was acceptable, and the water could be drunk following disinfection. This spectrum of F^- can stop tooth decay by promoting dental enamel remineralization. The principal ingredients of NO_3^- entering the aquatic environment are urban effluent discharge and livestock excretion of nitrogenous waste. Nitrogen fixation, air deposition, and agricultural runoff areas are examples of indirect inputs (Ravi *et al.,* 2020). The suggested NO_3^- concentration for drinking water is 45 mg/l. The findings showed that the nitrate concentration was between 1.29 and 2.70 mg/l. It is explainedthat the region's two most significant economic drivers are industrial production and agricultural cultivation, both of which have attracted migrants. These can be considered two potential sources of pollution in the region as a result. Since Fe^{2+} helps blood flow, it is not thought that the concentration found poses a health risk. DNA deterioration can also be encouraged by loose intracellular iron. Iron-rich water that has been concentrated can, however, cause turbidity to rise and turn reddish brown. The iron concentration fluctuates from 0.60 to 2.61 mg/l during the study period, which is within the permitted range of 1 mg/l. Figure 4a-t shows a great distinction between polluted and unpolluted water sample properties that may be indicative of a non-point source (NPS) pollution. In the existing research,two indexing mechanisms namely WA-WQI and SWARA-WQI and three MCDM methods such as CP, OWA and CoCoSo were used to examine the WQI.

These methods were used while taking 20 physicochemical factors into consideration. The obtained WA-WQI range is 23.78-96.09, suggesting categories ranging from 'good' to 'very poor' (Table 1). These values were interpolated across the whole research to produce a map in ArcGIS 10.5 (Figure 5). For the study, SWARA-WQI was additionally used for the assessment of water quality. It values (Table 1) varied in the range 14.6-1065.2. These values signified that the water quality was excellent to extremely poor. The highest WQI value generated from both stated approaches was scrutinized at SP-(9) which had elevated amounts of TC, TKN, EC, SAR, TDS, TH, Cl^-, $SO_4{}^{2-}$ and Fe^{2+}. According to WA-WQI values, 15.78 % and 68.42 % of the selected locations had excellent to good water quality, whereas 15.79 % had poor or very poor water quality. In case of SWARA-WQI, approximately 84.21% of samples fall in excellent range, implying for drinking purposes. Around 15.79% ranged into poor or very poor category. Using the IDW in Figure 6, SWARA-WQI variability theme maps were created for the research region. Three locations (SP-8, 9 and 19) out of the total 19 samples reported poor or very poor quality WQI values; this observation may be the result of the area's careless handling of household, industrial, and industrial effluents. Although the river runs through the city's periphery, all sites had very high TKN and TC readings, which may indicate pollution from neighbouring domestic and agricultural operations. If existing procedures are maintained, the situation will worsen as more surface water samples in the future will fall into the marginal and poor categories (Das, A, 2023).




(e) TSS
Legend
Sampling Points (SN)
Mahanadi River Basin
TSS
<VALUE>
28.7 - 40.2
40.3 - 51.8
51.9 - 63.3
63.4 - 74.9
(f) Alkalinity (Al)
Legend
Sampling Points (SN)
Mahanadi River Basin
Alkalinity
<VALUE>
70.4 - 78
78.1 - 85.6
85.7 - 93.2
93.3 - 101
(g) COD
Legend
Sampling Points (SN)
Mahanadi River Basin
COD
<VALUE>
6.763 - 9.732
9.733 - 12.7
12.71 - 15.67
15.68 - 18.64
(h) Ammoniacal Nitrogen
Legend
Sampling Points (SN)
Mahanadi River Basin
Ammoniacal N
<VALUE>
0.5101 - 0.6843
0.6844 - 0.8585
0.8586 - 1.033
1.034 - 1.207
N
Sundergarh
Jharsuguda
Brajarajnagar(D/s)
Brajarajnagar(U/s)
Sambalpur
Hirakud
Dhama
Sonepur(U/s)
Ulunda
Sonepur(D/s)
Boudh
Athamalik
Narsinghpur
Tikarpada
Tigiria
Cuttack(D/s)
Cuttack(U/s)
Choudwar(D/s)
Paradeep
0 60 120 240 360 480
Km


(i) free ammonia
Legend
Sampling Points (SN)
Mahanadi River Basin
FreeNH3
<VALUE>
0.02 - 0.026
0.02601 - 0.032
0.03201 - 0.038
0.03801 - 0.04399
Sundergarh
Jharsuguda
Brajarajnagar(D/s)
Brajarajnagar(U/s)
Sambalpur
Hirakud
Dhama
Sonepur(U/s)
Ulunda
Sonepur(D/s)
Boudh
Athamalik
Narsinghpur
Tikarpada
Tigiria
Cuttack(D/s)
Cuttack(U/s)
Choudwar(D/s)
Paradeep
0 60 120 240 360 480 Km
(j) TKN
Legend
Sampling Points (SN)
Mahanadi River Basin
TKN
<VALUE>
3.31 - 5.44
5.45 - 7.56
7.57 - 9.68
9.69 - 11.8
0 60 120 240 360 480 Km
(k) EC
Legend
Sampling Points (SN)
Mahanadi River Basin
EC
<VALUE>
138.1 - 2,041
2,042 - 3,943
3,944 - 5,845
5,846 - 7,748
0 60 120 240 360 480 Km
(l) SAR
Legend
Sampling Points (SN)
Mahanadi River Basin
SAR
<VALUE>
0.411 - 4.45
4.46 - 8.5
8.51 - 12.5
12.6 - 16.6
0 60 120 240 360 480 Km



(m) Boron
Legend
Sampling Points (SN)
Mahanadi River Basin
B
<VALUE>
0.03 - 0.16
0.1601 - 0.2899
0.29 - 0.4199
0.42 - 0.5499
(n) TDS
Legend
Sampling Points (SN)
Mahanadi River Basin
TDS
<VALUE>
82.7 - 3,370
3,380 - 6,660
6,670 - 9,940
9,950 - 13,200
(o) TH
Legend
Sampling Points (SN)
Mahanadi River Basin
TH
<VALUE>
51.2 - 587
588 - 1,120
1,130 - 1,660
1,670 - 2,190
(p) Cl
Legend
Sampling Points (SN)
Mahanadi River Basin
Cl
<VALUE>
9.7 - 1,200
1,300 - 2,500
2,600 - 3,700
3,800 - 4,900
Sundergarh
Jharsuguda
Brajarajnagar(D/s)
Brajarajnagar(U/s)
Sambalpur
Hirakud
Dhama
Sonepur(U/s)
Ulunda
Sonepur(D/s)
Athamalik
Boudh
Narsinghpur
Tikarpada
Tigiria
Cuttack(D/s)
Cuttack(U/s)
Choudwar(D/s)
Paradeep
0 60 120 240 360 480
Km

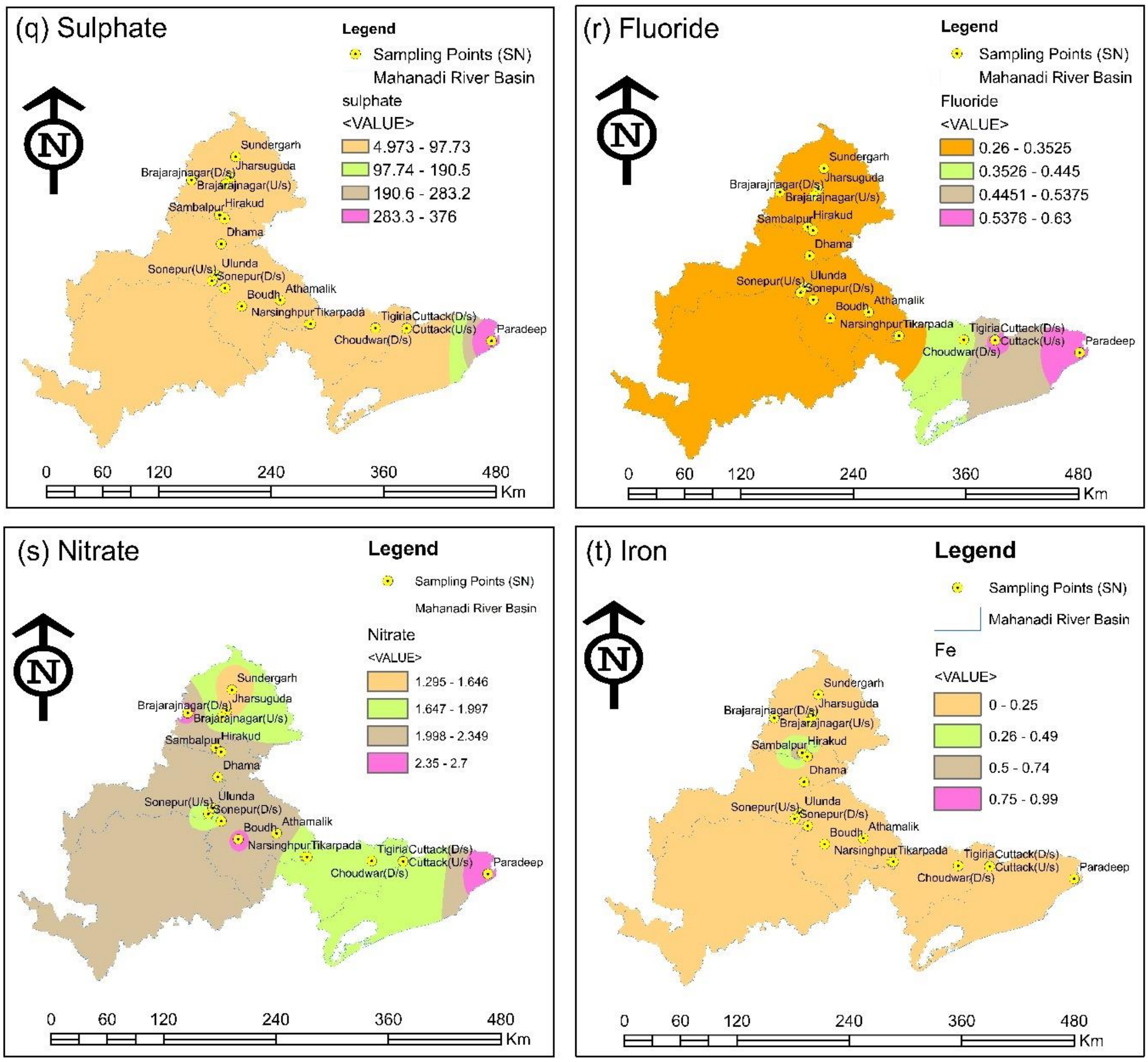


Figure 4: *Surface water quality spatial distribution of parameters (a) pH, (b) DO, (c) BOD, (d) TC, (e) TSS, (f) Alkalinity, (g) COD, (h) NH_3-N, (i) Free-NH_3, (j) TKN, (k) EC, (l) SAR, (m) B^+, (n) TDS, (o) TH, (p) Cl^-, (q) SO_4^{2-}, (r) F^-, (s) NO_3^- and (t) Fe^{2+}*

Three MCDM techniques, including OWA, CP, and CoCoSo, were used to resolve any inconsistencies between the basic WQI method and the three MCDM techniques in order to comprehend the river's pollution levels. Ranking the sampling locations of a waterbody according to their relative pollution levels is a vital indicator for programmes that monitor water quality issues. All the water quality metrics were subjected to these procedures in order to create overall rankings, with the highest rank for each time denoting the most polluted sample location. It is a helpful tool for making decisions. Table 1 displays the sampling locations' performance score and ranks. Figures 7, 9, and 11 show how OWA, CoCoSo, and CP vary among the sites. OWA, CP, and CoCoSo values were interpolated throughout the whole study region to construct an index map in ArcGIS for Figures 8, 10, and 12. In compared to other places, the sampling location SP-(9) was the most contaminated during the study period, followed by SP-8 and SP-19. It is evident that from the analysis at St. 9 that TC, TKN, EC, SAR, TDS, TH, Cl^-, SO_4^{2-} and Fe^{2+} had high values relative to their desirable drinking water guidelines. Most of the places in the upper reaches of the river that received lower rankings across all metrics were surrounded by rural areas with low population densities and few human activities (mostly agricultural activities were observed). These positions are crucial because they allow for the prioritization of policy decisions and river restoration efforts. Poor water quality indicates the existence of a significant quantity of contaminants from the clothing sector and related corporate wastewater, dumping of sewage, and intensive agricultural runoff, although it is still safe to drink untreated. In order to compare the rating processes, three decision-making tools are consequently offered in this ongoing research. In order to evaluate the water quality and compute semi variogram models for each of the parameters, the output of every model (spherical, circular, exponential and Gaussian) in the Kriging method were employed to generate a map that has the least amount of error for each measure of water quality (Ligate *et al.*, 2021). The Gaussian model was regarded as the best-fit semi-variogram model for the WA-WQI and SWARA-WQI datasets based on the results (Table 2). The Gaussian model's RMSE and ASE values, which were respectively 12.07 and 7.85 for the WA-WQI and 193.45 and 68.81 for the SWARA-WQI, were the lowest of all the models. It is evident from themaps that were acquired (Figure 13) that the majority of the metrics in the SP-(9) region had bigger values suggestingincreased pollution. The activity of factories close to the riverand the discharge of sewage into it may be the cause. The nugget/sill ratio is typically used in our study to show spatialdependence. For both indices, the nugget/sill values of 0.12 and 0.017 have been determined. Additionally, both indices exhibit a significant spatial dependence, indicating that chemical fertilizers and industrial waste water discharge are likely impacting the water quality (Ijumulana *et al.*, 2022).

Table 1: *Characterization of 19 survey stations for human consumption premised on WQI and MCDM values retrieved using different methods*

Sample No	WA WQI	Water type	SWARA WQI	Rank	Water type	OWA	Rank of OWA	CP	Rank of CP	CoCoSo	Rank of CoCoSo
SP-1	25.87	Excellent	15.69	16	Excellent	0.036	18	0.056	17	1.59	16
SP-2	30.72	Good	18.4	9	Excellent	0.042	9	0.066	8	2.06	9
SP-3	23.78	Excellent	16.21	15	Excellent	0.037	16	0.055	18	1.71	15
SP-4	30.21	Good	19.88	5	Excellent	0.044	4	0.068	5	2.27	4
SP-5	33.08	Good	18.58	8	Excellent	0.041	11	0.063	12	1.93	12
SP-6	31.59	Good	19.47	6	Excellent	0.041	10	0.064	10	2.04	10
SP-7	33.47	Good	17.61	12	Excellent	0.04	12	0.062	13	2.02	11
SP-8	52.63	Poor	196	2	Poor	0.076	2	0.128	2	3.9	2
SP-9	96.09	Very poor	1065.2	1	Extremely Poor	0.909	1	0.934	1	25.48	1
SP-10	35.9	Good	14.97	18	Excellent	0.038	15	0.06	14	1.46	18
SP-11	27.08	Good	15.08	17	Excellent	0.035	19	0.054	19	1.26	19
SP-12	29.6	Good	14.55	19	Excellent	0.037	17	0.058	16	1.74	14
SP-13	30.41	Good	16.93	13	Excellent	0.04	13	0.063	11	1.91	13
SP-14	28.41	Good	19.98	4	Excellent	0.044	6	0.068	6	2.27	5
SP-15	25.16	Excellent	16.32	14	Excellent	0.038	14	0.058	15	1.55	17
SP-16	35.33	Good	18.35	10	Excellent	0.044	5	0.068	4	2.17	7
SP-17	33.1	Good	19.45	7	Excellent	0.042	8	0.066	9	2.11	8
SP-18	36.43	Good	17.91	11	Excellent	0.043	7	0.067	7	2.18	6
SP-19	52.25	Poor	152	3	Poor	0.063	3	0.1	3	3.4	3

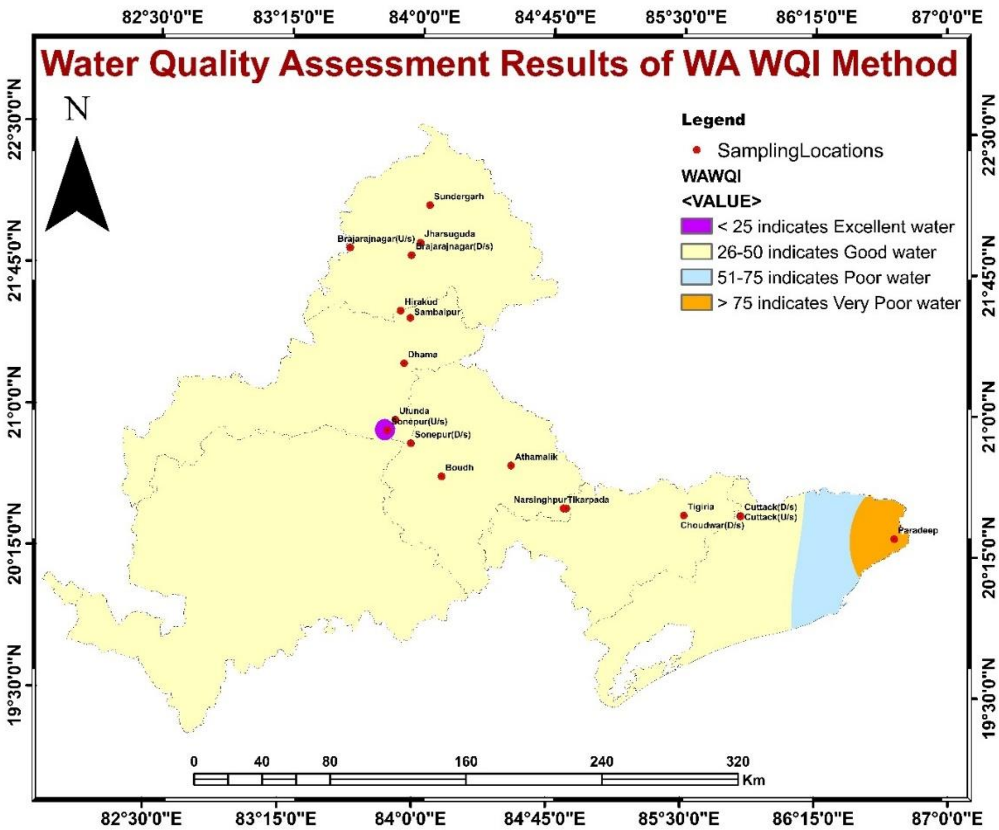


Figure 5: *Spatial distribution of WA WQI map based on categorization of surface water samples*

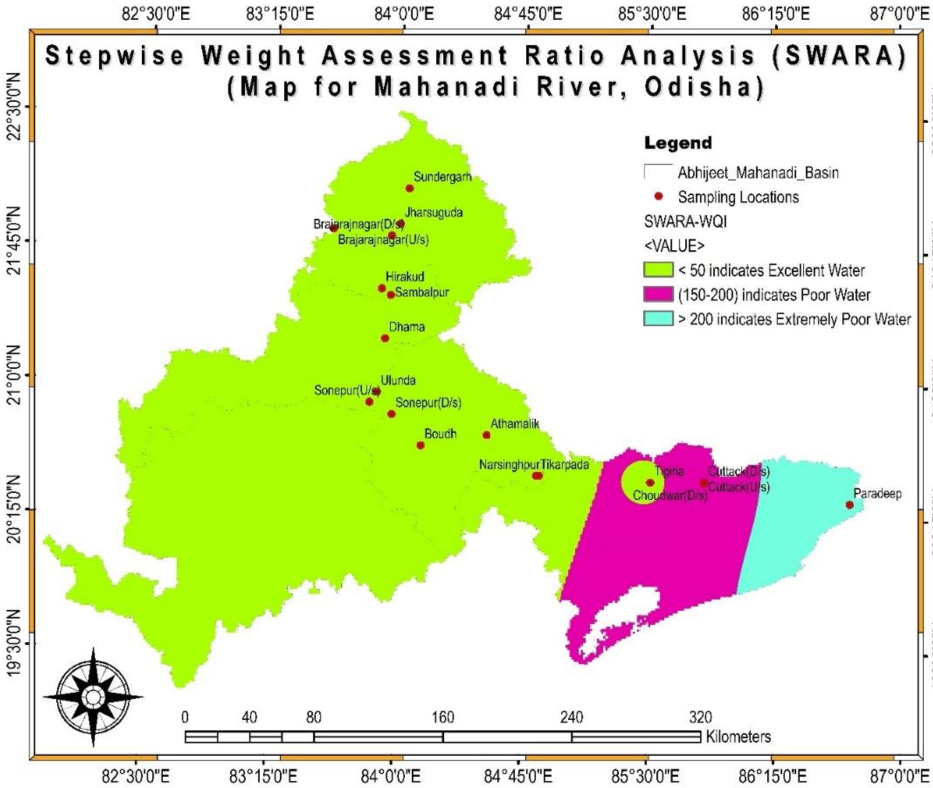


Figure 6: *Geospatial distribution map using SWARA WQI approach*

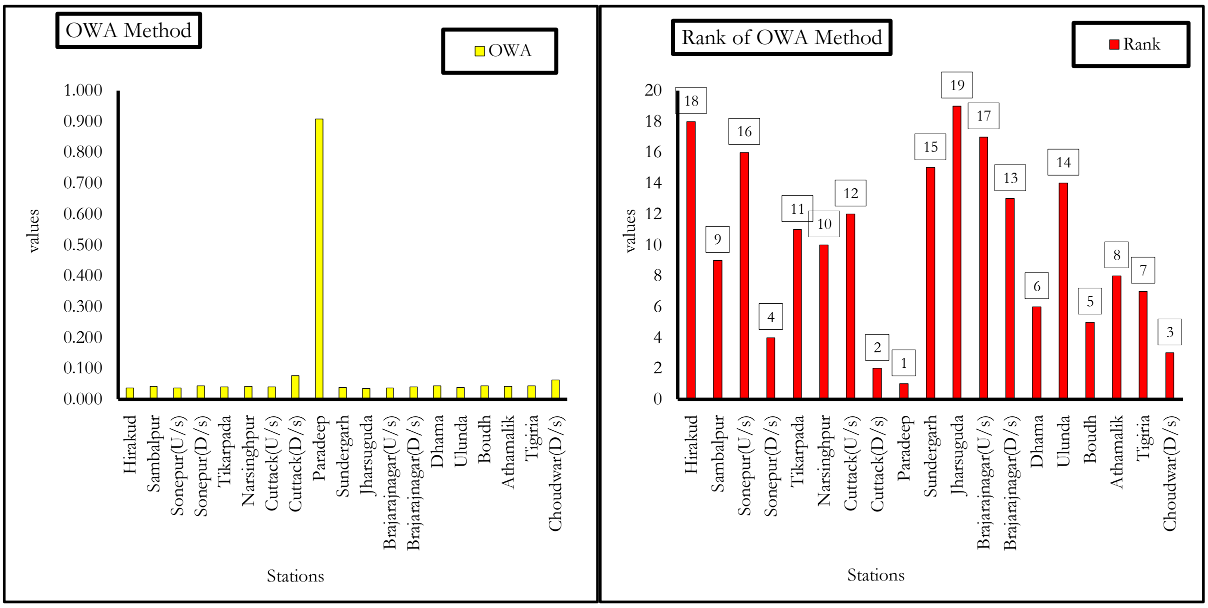


Figure 7: *Variation and rating of all quality monitoring points based on OWA*

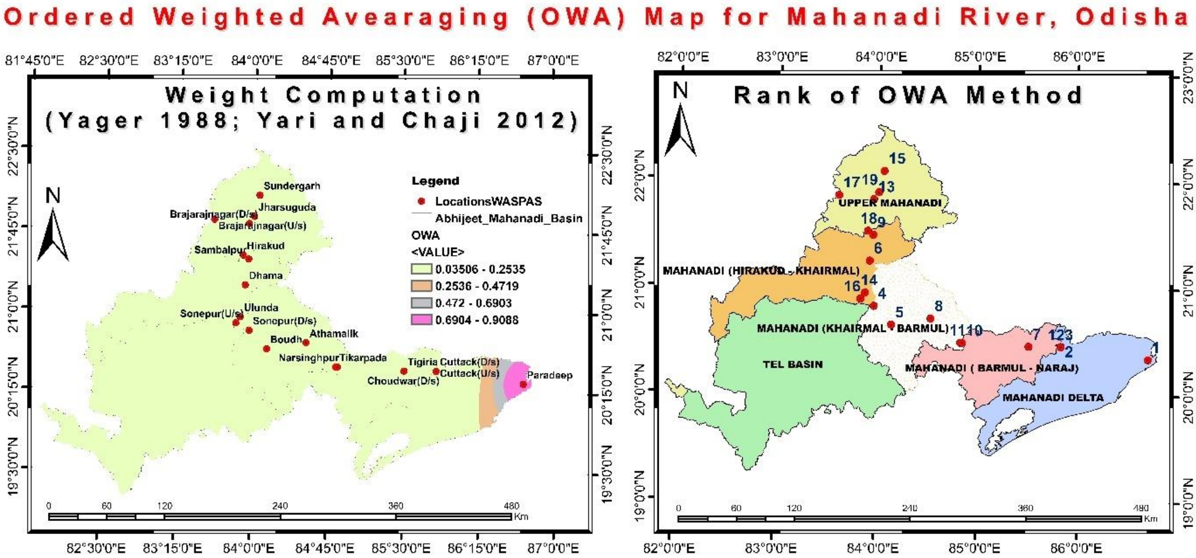


Figure 8: *OWA map of the investigated areas and measuring points*

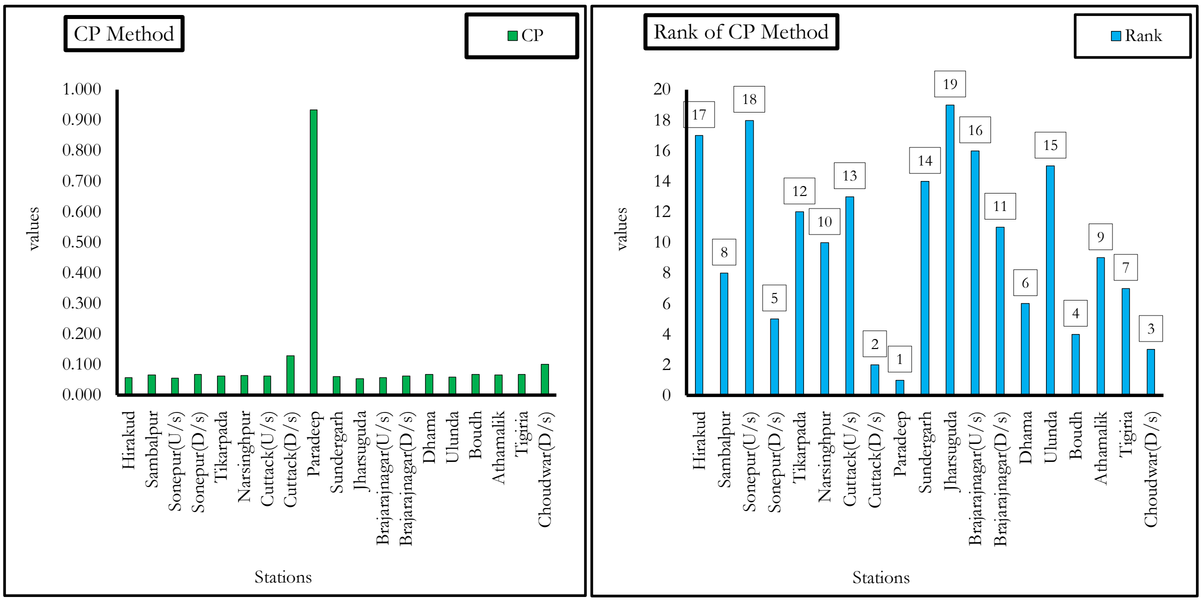


Figure 9: *Variation and rating of all quality monitoring points based on Compromise Programming (CP)*

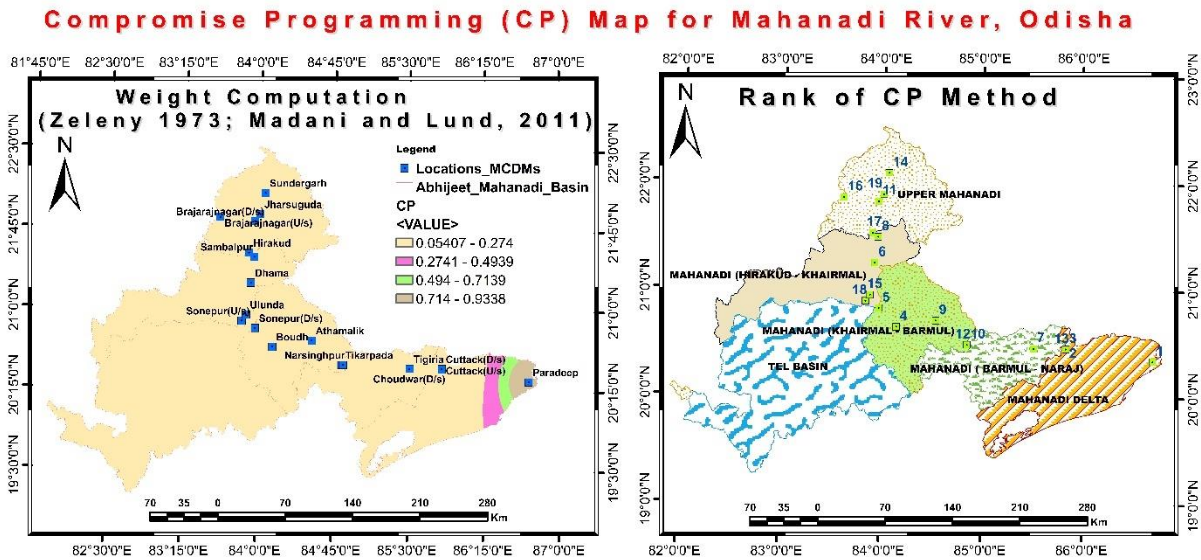


Figure 10: *Spatial distribution map of CP method*

Proceedings DOI: 10.21467/proceedings.160
ISBN: 978-81-965621-9-9
Series: AIJR Proceedings
ISSN: 2582-3922

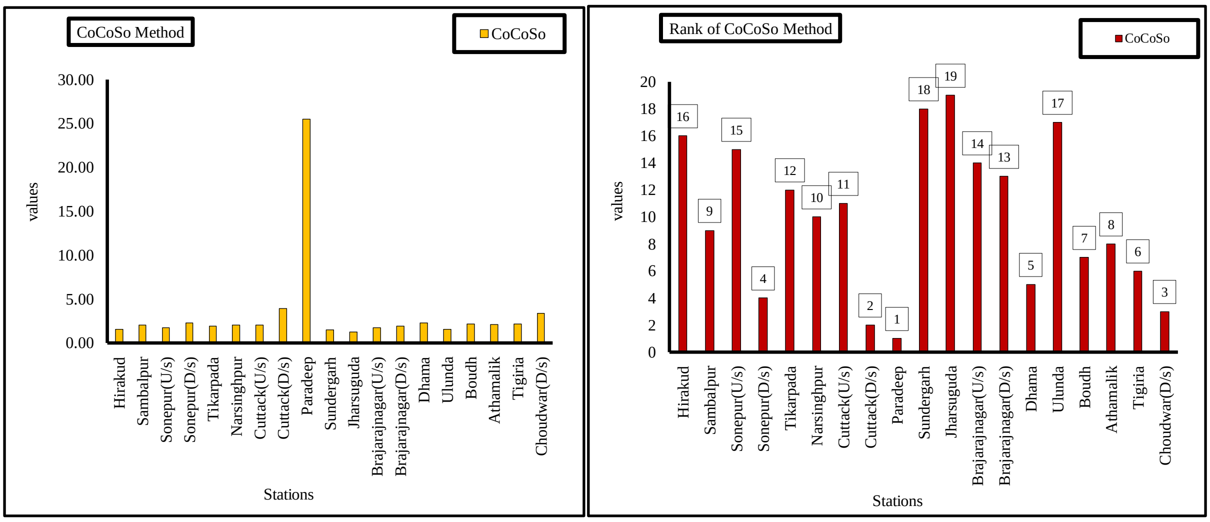


Figure 11: *Variation and rating of all quality monitoring points based on Combined Compromise Solution (CoCoSo)*

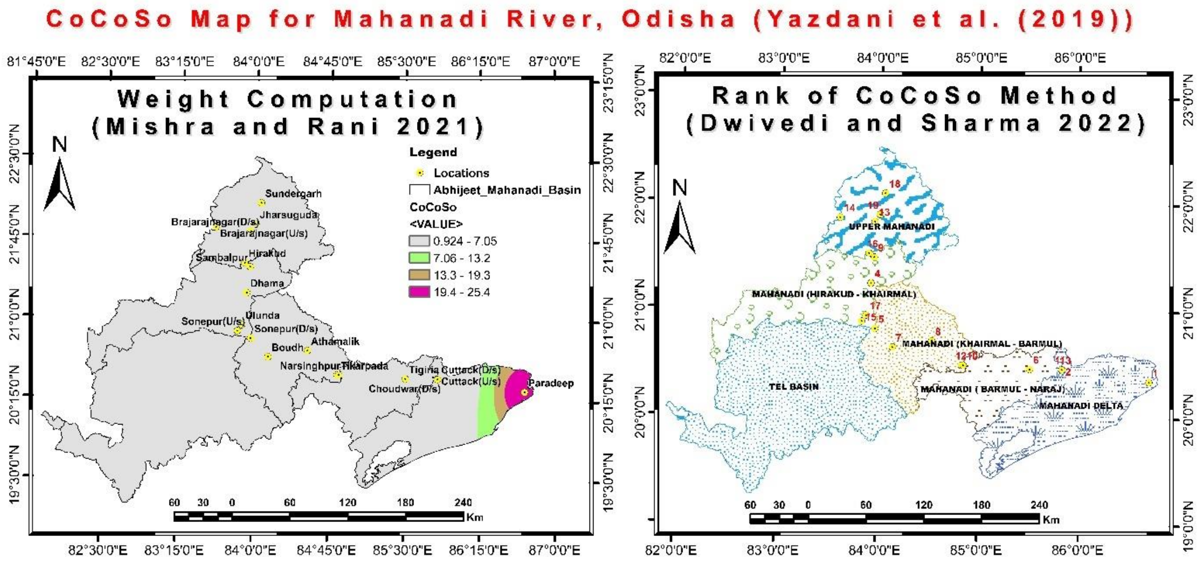


Figure 12: *CoCoSo map of the study region*

Table 2: *Description of the surface water quality parameters' best-fitting variogram model*

	Models Outline	Score of Nugget	Sill value	Nugget/sill	Value of ASE	Readings of RMSE	Score of MSE	Value of RMSSE
WA WQI	Circular	95.67	91.71	1.04	11.08	13.63	-0.03	1.08
	Spherical	99.89	76.57	1.3	11.28	13.66	-0.03	1.07
	Exponential	115.28	83.01	1.39	12.44	13.86	-0.03	1.14
	Gaussian	43.6	361.5	0.12	7.85	12.07	-0.11	0.98
SWARA-WQI	Circular	5999	73663	0.08	124.06	224.41	-0.12	1.08
	Spherical	6342.3	66090.47	0.1	127.45	224.87	-0.12	1.05
	Exponential	7283.05	59900.06	0.12	146.86	229.99	-0.11	1.41
	Gaussian	2147.23	124816	0.02	68.81	193.45	-0.2	0.98

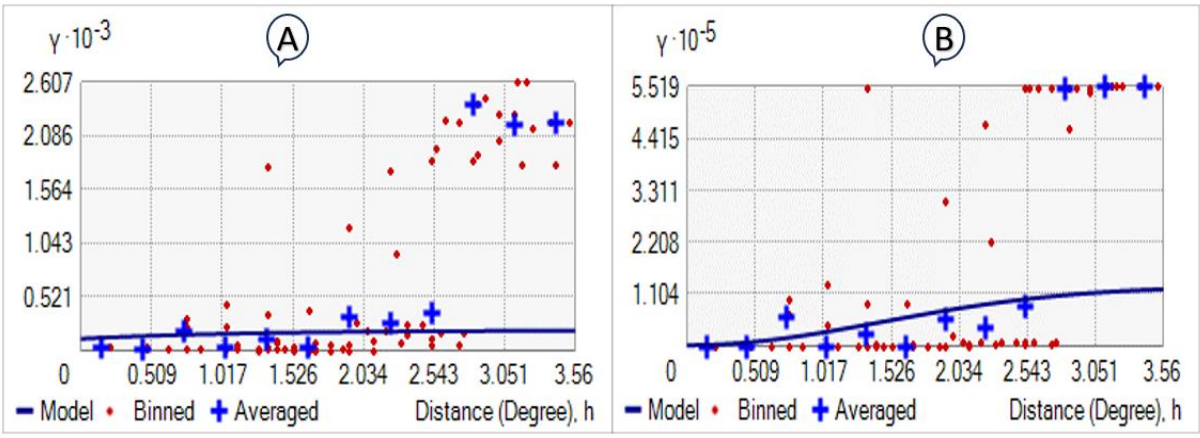


Figure 13: *The best-fit semi variogram models for (a) WA WQI and (b) SWARA-WQI*

6 Conclusion

This study examines the suitability of surface water quality inMahanadi Basin, Odisha, for drinking activities. Physical and chemical properties, geostatistical analysis, drinking water quality indices assisted with multi-criteria decision-making (MCDM) and Geographical Information System (GIS) techniques, were used to determine the quality of surface water suitable for human ingestion. Detailed evaluations of surface water quality for drinking systems were carried out employing Weighted Arithmetic (WA) and Stepwise Weight Assessment Ratio Analysis (SWARA) water quality indices (WQIs). As a result of the assessment, WA WQI grade (23.78-96.09) was assessment as excellent to very poor, while excellent to extremely poor zone comes under SWARA WQI (14.6-1065.2). The land use status of a basin has a significant impact on the water quality of a river, suggesting that pollution levels could be severe in some areas such as SP-(8), (9) and (19), which is subjected to extensive human activity. The main factors influencing such a high WQI were the TC and TKN. Finally, using GIS, all the spatial maps were layered, and an integrated result was produced to show how generally suitable surface water is for drinking. The overall integrated MCDM output (CP + OWA + CoCoSo) based on the 20 parameters showcases that SP-(9) is found to be the most polluted place, followed by SP-(8) and SP-(19), as compared to other locations. This was in line with the findings of the study, which showed that surface runoff from the dumpsite's low-lying section contributed to high values of TC, TKN, EC, SAR, TDS, TH, Cl-, SO_4^{2-} and Fe^{2+}. Municipal and household sewage inputs, as well as agricultural runoff, were the main sources of contamination. However, geostatistical results reveal Gaussian model found to be the best-fit among other semi-variogram models, in determining the smallest nugget/sill ratio, ASE and RSME. As a result, it lessens the impact of any judgement error brought on by the experts' subjective judgement of water quality. Overall, it can be said that the Mahanadi River's water quality is good (84.21%). It must be processed before being used in areas with extreme poverty. This method, which integrates physicochemical measurements, WQIs, and MCDM models, may be further researched to improve its accuracy for surface water under various circumstances. Decision-makers can better manage and safeguard the river with the information gleaned from this research.

7 Declarations

7.1 Acknowledgements

The State Pollution Control Board, water supply, Odisha is acknowledged by the writers for its physio-chemical interpretation of surface water. We appreciate the financial support provided by the research department at the C.V. Raman Global University in Bhubaneswar, India. Sincere appreciation is also due to the Editor and two anonymous reviewers for their helpful criticism and recommendations that enhanced the manuscript's draft report.

7.2 Publisher's Note

AIJR remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

How to Cite

Abhijeet Das (2023). Assessing Surface Water Quality for Drinking Water Supply using Hybrid GIS-Based Water Quality Index (WQI) in Mahanadi River Basin (MRB), Odisha, India. *AIJR Proceedings*, 1-21. https://doi.org/10.21467/proceedings.160.1

References

[1] A.R. Mishra, P. Rani, Assessment of sustainable third party reverse logistic provider using the single-valued neutrosophic Combined Compromise Solution framework, Clean. Respons. Consump. 2 (2021) 100011, https://doi.org/10.1016/j. clrc.2021.100011.

[2] Anand, B., Karunanidhi, D., Subramani, T., Srinivasamoorthy, K., & Suresh, M. (2020). Long- term trend detection and spatiotemporal analysis of groundwater levels using GIS techniques in Lower Bhavani River basin, Tamil Nadu, India. Environment, Development and Sustainability, 22(4), 2779–2800.

[3] Angello, Z.A., Tr¨anckner, J., Behailu, B.M., 2020.Spatiotemporal evaluation and quantification of pollutant source contribution in little Akaki river, Ethiopia: conjunctive application of factor analysis and multivariate receptor model. Pol. J. Environ. Stud.30 (1), 23–34.https://doi.org/10.15244/pjoes/119098.

[4] APHA, 2005. Standard Methods for the Examination of Water and Wastewater, twenty first ed. American Public Health Association, Washington.

[5] Bastia, F., Equeenuddin, S., Roy, P. D., and Hernández-Mendiola, E. (2020). Geochemical signatures of surface sediments from the Mahanadi River basin (India): chemical weathering, provenance, and tectonic settings. Geol. J. 55, 5294–5307. doi: 10.1002/gj.3746.

[6] Brown RM, McClelland NI, Deininger RA, Tozer RG (1970) A water quality Index- do we dare. WaterSew Works 117:339–343.

[7] Bui, D., Khosravi, K., Tiefenbacher, J., Nguyen, H.,Kazakis, N., 2020. Improving prediction of water quality indices using novel hybrid machine-learningalgorithms. Sci. Total Environ. 721, 137612.

[8] Cho YC, Choi HM, Ryu IG, Kim SH, Shin DS, Yu SJ (2021) Assess ment of water quality in the lowerreaches Namhan river by using statistical analysis and water quality index (WQI). J Korean Soc WaterEnviron 37:114–127. https:// doi. org/ 10. 15681/ KSWE. 2021. 37.2. 114.

[9] Das, A. (2022). Multivariate statistical approach forthe assessment of water quality of Mahanadi basin, Odisha. Materials Today: Proceedings.

[10] Das, A. (2023). Anthropogenic Effects on Surface Water Quality Assessment in Baitarani River Basin, Odisha Using GIS and MCDM Techniques. Engineering Research Transcripts, 5, 37–64. https://doi.org/10.55084/grinrey/ERT/978-81-964105-3-7_4

[11] Das, A. (2023). Assessment of potability of surface water and its health implication in Mahanadi Basin, Odisha. Materials Today: Proceedings.

[12] Das, A. (2023). Identification of Surface Water Contamination Zones and its Sources on Mahanadi River, Odisha Using Entropy-Based WQI and MCDM Techniques. Engineering Research Transcripts, 4, 67–92. https://doi.org/10.55084/grinrey/ERT/978-81-964105-1-3_5

[13] Das, A. (2023). Modelling of Surface Water Quality and Spatial Mapping in Mahanadi Basin, Odisha. Journal of Mines, Metals and Fuels, 71(9), 1155–1173. https://doi.org/10.18311/jmmf/2023/35432

[14] Das, A. (2023). Water Criteria Evaluation for Drinking Purposes in Mahanadi River Basin, Odisha. In: Al Khaddar, R., Singh, S.K., Kaushika, N.D., Tomar, R.K., Jain, S.K. (eds) Recent Developments in Energy and Environmental Engineering. TRACE 2022. Lecture Notes in Civil Engineering, vol 333. Springer, Singapore. https://doi.org/10.1007/978-981-99-1388-6_20

[15] Das, A. (2024). Surface Water Quality Modelling Using Water Quality Index (WQI) and Geographic Information System (GIS) on the Mahanadi Basin, Odisha. In: Saxena, S., Shukla, S., Mural, P.K.S. (eds) Emerging Materials and Technologies in Water Remediation and Sensing. ICWT 2022. Lecture Notes in Civil Engineering, vol 439. Springer, Singapore. https://doi.org/10.1007/978-981-99-6762-9_2

[16] Das, A. 2023. 14th International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT, 2023-June, pp. 1043–1055

[17] Dash S, Kalamdhad AS (2021) Discussion on the existing methodol- ogy of entropy-weights in waterquality indexing and proposal for a modification of the expected conflicts. Environ Sci Pollut Res 28(38):53983–54001.

[18] de Souza, R.M., Seibert, D., Quesada, H.B., de Jesus Bassetti, F., Fagundes-Klen, M.R., Bergamasco, R., 2020. Occurrence, impacts and general aspects of pesticides in surface water: a review. Process Saf. Environ. Protect. 135, 22–37.

[19] Drasovean, R., Murariu, G., 2021. Water Quality Parameters and Monitoring Soft Surface Water Quality Using Statistical Approaches. Promising Techniques for Wastewater Treatment and Water Quality Assessment, p. 217.

[20] Gao, Y.Y., Qian, H., Ren, W.H., Wang, H.K., Liu, F.X., Yang, F.X., 2020. Hydrogeochemical characterization and quality assessment

of groundwater based on integrated-weight waterquality index in a concentrated urban area. J. Clean.Prod. 260, 121006.

[21] Gebere, A., Kawo, N.S., Karuppannan, S., Hordofa,A.T., Paron, P., 2021. Numerical modeling of groundwater flow system in the Modjo River catchment, Central Ethiopia. Model. Earth Syst. Environ. 7(4),2501–2515. https://doi.org/10.1007/s40808-020-01040-0.

[22] Gupta, S. (2022). AHP-based multi-criteria decision-making for forest sustainability of lower Himalayan foothills in northern circle, India—a casestudy. Environmental Monitoring and Assessment, 194(12), 1– 11. https://doi.org/10.1007/s10661-022-10510-0

[23] Holcomb, D.A., Stewart, J.R., 2020. Microbial indicators of fecal pollution: recent progress and challenges in assessing water quality. Current environmental health reports 7, 311–324.

[24] Horton, R.K. 1965. An index number system for rating water quality. J. Water. Pollut. Control Fed. 37:300-306.

[25] Hussen, A.M.E.A., Retnaningdyah, C., Hakim, L., Soemarno, S., 2018. The variations of physical and chemical water quality in coban rondo waterfall, malang Indonesia. In: AIP Conference Proceedings. AIP Publishing LLC, 050011.

[26] Ijumulana, J., Ligate, F., Irunde, R., Bhattacharya, P., Ahmad, A., Tomašek, I., *et al.* (2022). Spatial variability of the sources and distribution of fluoridein groundwater ofthe Sanya alluvial plain aquifers in northern Tanzania. Sci. Total Environ. 810:152153.doi: 10.1016/j.scitotenv.2021.152153.

[27] Islam, A.R.M.T., Mamun, A.A., Rahman, M.M., Zahid, A., 2020. Simultaneous comparison of modified-integrated water quality and entropy weighted indices: implication for safe drinking water in the coastal region of Bangladesh. Ecol. Indic. 113, 106229.

[28] Islam, M.A., Khan, R.H., Syeed, M., 2020. A smart and integrated surface water monitor system architecture: Bangladesh perspective. In: Proceedings of the International Conference on Computing Advancements, pp. 1–6.

[29] Jampani, M., Liedl, R., Hülsmann, S., Sonkamble, S., Amerasinghe, P., 2020. Hydrogeochemical and mixing processes controlling groundwaterchemistry in a wastewater irrigated agricultural system of India. Chemosphere 239, 124741.

[30] Jia, H., Qian, H., Zheng, L., Feng, W.W., Wang, H.K., Gao, Y.Y., 2020. Alterations to groundwater chemistry due to modern water transfer for irrigationover decades. Sci. Total Environ. 717, 137170.

[31] Karuppannan, S., Panneerselvam, B., Haji, M., Murugesan, B., Shube, H., Serre Kawo, N., 2022. Evaluation of Groundwater Quality and Its Suitability for Drinking and Cultivation Practices inand around the Deltaic Regions of South India Using DWQI, IWQI, and GIS. Climate Change Impact onGroundwater Resources. Springer, Cham, pp. 181– 200. https://doi.org/10.1007/978-3-031-04707- 7_10.

[32] Laltu, A. D. (2023). Drinking Suitability and Source Apportionment of Physical Parameters in Surface Water in Mahanadi Basin, Odisha. Odisha (April 14, 2023).

[33] Ligate, F., Ijumulana, J., Ahmad, A., Kimambo, V.,Irunde, R., Mtamba, J. O., *et al.* (2021). Groundwater resources in the East African Rift Valley: Understanding the geogenic contamination and water quality challenges in Tanzania. Sci. Afr. 13:e00831. doi: 10.1016/j.sciaf.2021.e00831.

[34] M. Alimardani, S. Hashemkhani Zolfani, M.H. Aghdaie, J. Tamoˇsaitien ˙e, A novel hybridSWARA and VIKOR methodology for supplier selection in an agile environment, Technol. Econ. Dev. Econ. 19 (2013) 533–548.

[35] M. Yazdani, P. Zarate, E.K. Zavadskas, Z. Turskis, A Combined Compromise Solution (COCOSO) method for multi-criteria decision-makingproblems, Manag. Decis. 57 (2019) 2501–2519

[36] Madani, K., Lund, J.R., 2011. A Monte-Carlo gametheoretic approach for multi- criteria decisionmaking under uncertainty. Adv. Water Resour. 34 (5), 607e616.

[37] Moussa, A., Chandoul, S., Mzali, H., Salem, S., Elmejri, H., Zouari, K., Hafiane, A., Mrabet, H., 2020. Hydrogeochemistry and evaluation ofgroundwater suitability for irrigation purpose in the Mornag region, northeastern Tunisia. Environ. Dev.Sustain.

[38] Muthusamy, B., Sithu, G.D.S., Ramamoorthy, A., Shankar, K., Gnanachandrasamy, G., Monica, C., Xiaozhong, H., 2022. Isotopic signatures,hydrochemical and multivariate statistical analysis of seawater intrusion in the coastal aquifers of Chennai and Tiruvallur District, Tamil Nadu, India.Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2021.113232.

[39] Naseem A, Ishak MIS, Ahmad MI, Umar K, YusuffMSMd, Anees MT, Qadir A, Almanasir YKA (2021) Modification of the water quality index (WQI) process for simple calculation using the multi-crite- ria decision-making (MCDM) method: a review. Water 13:905. https:// doi. org/ 10. 3390/ w1307 0905.

[40] Nong, X.Z., Shao, D.G., Zhong, H., Liang, J.K., 2020. Evaluation of water quality in the South-to- North Water Diversion Project of China using the water quality index (WQI) method. Water Res. 178,115781.

[41] Omer, N.H., 2019. Water quality parameters. Water quality-science, assessments and policy 18, 1–34.

[42] Paital, B., & Das, K. (2021). Spike in pollution to ignite the bursting of COVID-19 second wave is more dangerous than spike of SAR-CoV-2 under environmen- tal ignorance in long term: A review. Environmental Science and Pollution Research. https:// doi. org/ 10. 1007/ s11356- 021- 15915-x.

[43] Panda, S., Mallik, C., Nath, J., *et al.* (2020a). A study on variation of atmospheric pollutants over Bhubaneswar during imposition of nationwidelockdown in India for the COVID-19 pandemic. AirQuality, Atmosphere and Health, 14(1), 97–108.

[44] Panneerselvam, B., Muniraj, K., Pande, C., Ravichandran, N., Thomas, M., Karuppannan, S., 2021. Geochemical evaluation and human health risk assessment of nitrate-contaminated groundwater in an industrial area of South India. Environ. Sci. Pollut. Res.https://doi.org/10.1007/s11356-021-17281-0.

[45] Park S, Lee M, Park K, An Y (2020) Calculating virtual water for international water transactions: deriving water footprints in South Korea. J Korea Water Resour Assoc 53:765–772. https:// doi. org/ 10. 3741/ JKWRA. 2020. 53.S- 1. 765.

[46] Rashidi, F., & Shari?an, S. (2022). A comparative analysis of three multi-criteria decision-making methods for land suitability assessment. Environmental Monitoring and Assessment, 194(9),1–15. https://doi.org/10.1007/s10661-022-10259-6.

[47] Rath, S., Bal, A., & Paital, B. (2021). Heavy metal and organic load in Haripur creek of Gopalpur alongthe Bay of Bengal, east coast

of India.Environmental Science and Pollution Research International, 28(22), 28275– 28288. https:// doi. org/ 10. 1007/ s11356- 021-12601-w

[48] S.H. Zolfani, J. Saparauskas, New application of SWARA method in prioritizing sustainability assessment indicators of energy system, Eng. Econ.24 (2013) 408–414.

[49] Shankar, K., Kawo, N.S., 2019. Groundwaterquality assessment using geospatial techniques and WQI in North East of Adama Town, Oromia Region, Ethiopia. Hydrospat. Anal. 3 (1), 22–36. https://doi.org/10.21523/gcj3.19030103.

[50] Silvestri L, Forcina A, Di Bona G, Silvestri C (2021) Circular economy strategy of reusing olive mill wastewater in the ceramic industry: how the plant location can benefit environmental and economic performance. J Cleaner Prod 326:129388. https:// doi. org/ 10. 1016/j. jclep ro. 2021. 129388.

[51] Singh KR, Dutta R, Kalamdhad AS, Kumar B (2020) Review of exist- ing heavy metalcontamination indices and development of an entropy-based improved indexing approach.Environ Dev Sustain 22(8):7847–7864.

[52] Sunkari, E.D., Abu, M., Zango, M.S., Lomoro Wani, A.M., 2020. Hydrogeochemicalcharacterization and assessment of groundwater quality in the Kwahu-Bombouaka Group of the Voltaian Supergroup, Ghana. J. Afr. Earth Sci. 169 (November 2019), 103899 https://doi.org/10.1016/j.jafrearsci.2020.103899.

[53] Uddin, M.G., Nash, S., Olbert, A.I., 2021. A review of water quality index models and their use for assessing surface water quality. Ecol. Indicat. 122, 107218 https://doi. org/10.1016/j.ecolind.2020.107218.

[54] V. Ker˘sulien ˙e, Z. Turskis, integrated fuzzy multiple criteria decision making model for architect selection, Technol. Econ. Dev. Econ. 17 (2011) 645–666.

[55] Varol M (2020) Use of water quality index and multivariate statistical methods for the evaluation ofwater quality of a stream affected by multiple stressors: a case study. Environ Pollut 266:115417. https:// doi. org/ 10. 1016/j. envpol. 2020. 115417.

[56] Weibe, S.M.J., 2021. Assessment of Drinking Water Quality for Residents of Kuria West in Migori County. Ph.D. thesis. University of Nairobi

[57] WHO, Geneva. "Guidelines for drinking-water quality." World Health Organization 216 (2011): 303–304.

[58] Yager, R.R., 1988. On ordered weighted averaging aggregation operators in multi- criteria decision making, IEEE Transactions on Systems. Man Cybern. 18 (1), 183e190.

[59] Yari, G., Chaji, A., 2012. Determination of orderedweighted averaging operator weights based on the m-entropy measures. Int. J. Intelligent Syst. 27 (12),1020e1033. https://doi.org/10.1002/int.21559.

[60] Zeleny, M., 1973. Compromise programming. In: Cochrane, J.L., Zeleny, M. (Eds.), Multiple CriteriaDecision Making. University of South Carolina Press, Columbia, South Carolina.

[61] Zhang, B., Zhao, D., Zhou, P., Qu, S., Liao, F. &Wang, G. 2020a Hydrochemical characteristics ofgroundwater and dominant water-rock interactions in the Delingha area, Qaidam Basin, Northwest China. Water 12(3), 836–853. doi:10.3390/ w12030836.