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A Novel Approach Combining Entropy-Water Quality Index (WQI) and Multi-Criteria Decision-Making (MCDM) Analysis for Monitoring Water Quality in Mahanadi River Basin, Odisha

Abhijeet Das[1] and Dr. Bhagirathi Tripathy[2]
[1]Department of Civil Engineering, C.V. Raman Global University (CGU), Bhubaneswar, Odisha, India
Email: das.abhijeetlaltu1999@gmail.com
ORCID ID: https://orcid.org/0000-0003-4599-5462
[2]Department of Civil Engineering, I.G.I.T, Sarang, Dhenkanal, Odisha, India

***Abstract*—The severeness of pollution from non-point sources (NPS) was highlighted by the high amount of organic matter in the watersheds' downstream areas. The evaluation of the significant physical and chemical variables of 19 samples of surface water quality from the Mahanadi River Basin (MRB), Odisha and it demonstrated that, apart from TKN and TC, the majority of the parameter levels are below the WHO's recommended upper drinking limits. The dataset was submitted to a widely recognised coherence technique using the entropy water quality index (e-WQI) and Multi-Criteria Decision-Making analysis, entitled Additive Ratio Assessment (ARAS), to identify the spatial-temporal variation and its pollution source identification and apportionment. It is observed that samples mostly contained the anions Cl^- >SO_4^{2-}>NO_3^->F^-, while the primary cations were Fe^{2+}>B^+. For each of the sampling sites, e-WQI was calculated to be 14.55-1065.20, respectively. According to the e-WQI, most of the test locations were in the excellent to extremely poor zone. The results revealed that 84.21% samples excellent for drinking, 10.53% poor and 5.26% extremely poor and thus, unsuitable for consumption. Additionally, the main causes of the poor water quality at sites CS-8, 9 and 19 are industrial and agricultural inputs. However, a mathematical method called ARAS has been adopted to find a better alternative in estimating the level of ranking of pollution. It is adaptable, unbiased, simple to compute, and time-saving, and it will offer valuable details to prioritise and sustain the water quality of potable sources and lessen the effects of using low-quality surface water resources on human health. Moreover, the results showed that the score and its rank at CS-9, signified as mostly polluted site, in comparison to other locations. Long-term wastewater use, human actions, excessive surface water extraction, and modifications to land use patterns could all be contributing factors. The detection of elemental correlations is ultimately permitted by both e-WQI and ARAS, and their possible source was anthropogenic rather than natural. These results are crucial for comprehending the sustainability of surface water for drinking in the research area.**

***Index Terms*— Mahanadi River Basin, e-WQI, ARAS, industrial, agricultural, surface water extraction, sustainability.**

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I. INTRODUCTION

Water is one of the most precious resources on earth and is necessary for life to survive in its purest form (Ikram et al. 2022b). Historical data demonstrates that pressure from anthropogenic changes in water quality and quantity caused the disappearance of several human settlements (Dimple et al. 2022b). Additionally, the quality of surface water and groundwater around the world has declined due to a rise in urbanisation, construction, agricultural activities, industrial applications, and natural processes. This has had a negative influence on human health (Rajput et al. 2023). One of the necessities for human living on Earth is access to enough quantities and good quality of water, yet maintaining good water quality is difficult in the field of water resources monitoring (Vishwakarma et al. 2022; Das, A. 2022). Particularly in both arid or semi-arid sectors, surface water is frequently the only reliable source of fresh water supplies. It is also acts as the principal source of water for food, energy, and the ecosystem (Cooley et al. 2021). Further, the amount of dissolved elements in water is continually changing, culminating from both natural (rainfall, weathering, rock and soil erosion) and man-made practices namely residential and commercial (Gao et al. 2021). As an outcome, quality decline and a lack of resources are both obstacles to sustainable development (He et al. 2021). To ensure its health, a stringent and vigilant approach to monitoring and assessment is required (Singha et al. 2021). Therefore, the Water Quality Index (WQI) may be evaluated using a straightforward mathematical process that reduces a vast array of water characteristics to a single number that represents the sum of all water quality values (Masoud et al. 2022). Hence, WQI-based maps are simple to understand and help raise public awareness about water pollution. They also help enforce laws for proper waste management from various sources and place restrictions on surface water extraction, which in turn can help formulate effective management strategies for safeguarding water from contamination (Elsayed et al. 2021). The fact that this quantitative assessment approach requires expert knowledge in the distribution of variable weights in order to calculate the score, meaning that the true outcome is uncertain, is one of its most major shortcomings (Uddin et al. 2021). Many academics have looked into how to reduce the subjectivity of the WQI approach, which has shown to be a more precise and useful tool for exact weighing systems, by giving important ions weights based on entropy and finally computing an entropy WQI score (Marghade 2020; Alam et al. 2021). Multi-criteria decision making (MCDM) has been used to select the optimal option based on comparative evaluation of the available options in order to address the limitations of the entropy method (Patel et al. 2023). Therefore, this work suggests use an MCDM technique like Additive Ratio Assessment (ARAS). Additionally, this strategy has been employed in a variety of domains, including agriculture, water quality analysis, environmental catastrophe management, risk prioritisation, and human system dependability (Zavadskas 2012). The ARAS methodology will be used to select the best alternative and construct a ranking preference order of the options. This method is based on the same entropy analysis that is used to assess the weight of the criterion (Adali and Tusisik, 2016). However, it is crucial to put in place a workable and cost-effective plan for a reliable evaluation of water quality (Goswami and Mitra, 2020). Moreover, Geographical Information System (GIS) is used to evaluate and show spatial data, which helps with resource planning and environmental protection (Kadam et al. 2021b). The most popular spatial interpolation techniques are inverse distance weighting (IDW), Kriging, and Co-Kriging. It is a precise method that requires nearby points to have a greater influence on a point's assessed value than do points further away (Zhang et al. 2021). By creating weights of the various layers collected from the GIS environment, Gupta et al. (2022) coupled GIS with MCDM technique to advise decision-makers regarding appropriateness assessments of drinking water systems. The determination of weight coefficients utilising entropy based on the field data is the study's key concept (Akhtar et al. 2021). In view of this, the purpose to create a brand-new hybrid framework by incorporating WQI, MCDM, with the GIS-based strategy in order to give a brief overview on present surface water quality in rural-urban reach of Mahanadi basin region, in the State of Odisha, during summer period of 2020 till 2023 and its spatial variability at larger scales.

II. STUDY AREA

The Mahanadi River (Maha: great and Nadi: river), is one of the largest east-flowing, interstate rivers in Peninsular India, has its source at a height of 442 metres above mean sea level (MSL) close to the village of Pharsiya in the Chhattisgarh district of Dhamtari. It lies between latitude 19°21’N and 23°35’N and longitudes 80°30’E and 86°50’E. The river basin is in a tropical monsoon climate, with yearly average temperatures between 15.8°C and 28.7°C. The drainage basin has an average elevation of 426 m, a high elevation of 877 m, and a minimum height of 193 m (Das, A. 2022). The river provides a significant portion of the basin's 13590 Km^2 of irrigated land with water. Within the basin, agriculture is the most significant economic activity, and agricultural land use represents the most significant factors relative to other types of land use (Mohanty & Samanta, 2016). A part of the mineral belt with the highest concentration of iron ore, coal, limestone, dolomite, bauxite, lead, and copper is located inside the basin (Dileep et al. 2013). This river always has stagnant water in it from January to May each year, which contributes to the build-up of pollution in the area. Finally, during the rainy season, the filthy water is released into the Bay of Bengal (Panda et al. 2006). Figure 1 shows the locations and configuration of 19 quality monitoring sites.

III. Sampling Methodology

The surface water samples were carried out in summer season from 2020 till 2023. From the 19 existing measuring locations, a total of 20 surface water samples were taken. Water quality samples and assessments were made at every location along the river by considering the accepted procedures for examining water and wastewater (APHA, 2012). Evaluated parameters include Hardness (H), Total Coliform (TC), Dissolved oxygen (DO), Total Suspended Solids (TSS), Sulphate (SO_4^{2-}), Total dissolved solids (TDS), Fluoride (F^-), Alkalinity, Ammoniacal Nitrogen (NH_3-N), Total Kjeldahl Nitrogen (TKN), Electrical conductivity (EC), Boron (B), Free-ammonia (free-NH_3), Hydrogen Ion (pH), Sodium Adsorption Ratio (SAR), Iron (Fe^{2+}), Biochemical oxygen demand (BOD), Chemical oxygen demand (COD), Chloride (Cl^-), and Nitrate (NO_3^-). The units of the parameters were expressed in milligrams per litre (mg/l) except pH (non-dimensional) and EC (µS/cm at 25°C). The above parameters were crosschecked using ionic balance error (IBE) i.e., IBE = $[(\sum\text{cations} - \sum\text{anions})/(\sum\text{cations} + \sum\text{anions})] * 100$ for their accuracy to interpret chemical data, where the cations and anions are expressed in milligram per litre (mg/L). The IBE value should not go over the permitted limit of ± 5%. To create geodatabases and conduct a spatial inquiry, the current work used ArcGIS 10.5 software and the (IDW) approach.

IV. Methodology

An entropy-based WQI technique (e-WQI) has been used to calculate relative weights. Shannon established the idea of entropy method in 1948 (Shannon 1948), which measures unpredictability and disorderliness in the information. It calculates the index weight based on the degree of fluctuation in each index value, and deviation brought on by human factors can be avoided (Mishra and Rani, 2021). As a result, it is a useful method of presenting uncertainty and probability. The entropy is reduced when there is a significant difference between the evaluated parameters on a given indication, indicating that the indicator provides more useful information. On the other hand, the entropy increases when the difference is smaller. Entropy coefficient strategy can therefore be viewed as an object liberating technique. It is computed using the following equations as per (Marghade 2020). Based on the e-WQI, the surface water quality is characterized according to Wu et al. (2011), which symbolizes water with e-WQI<50 suggests 'excellent quality' water, e-WQI span from 50-100 represents as 'good', score of e-WQI ranged from 100 to 150 is taken as 'average', e-WQI value from 150 and 200 belongs to 'poor' and finally, e-WQI value>200 comes under 'extremely poor' category. ARAS, a multi-criteria decision-making method, was envisioned by Zavadskas (2012). It computes a weighted normalized matrix based on entropy weights and user-specified criteria in the presence of uncertainty. However, it is important to note that by evaluating the weight of each indicator separately, it is possible to identify the benefits and drawbacks of this procedure more easily for generating WQI for water quality evaluation (Ehsan et al. 2022; Nong et al. 2020). Since its introduction, this technique has grown in popularity for handling a variety of difficult decision-making issues, including security assessment, problems with determining the quality of water resources, and resource management (Torkayesh et al. 2021). Its procedural steps are ascertained as recommended by Adali and Tusisik, (2016).

V. Results and Discussions

The pH range in our experiment was 7.738–9.15, indicating that the water in the experimental sites was in excellent shape for drinking because the values fall within the acceptable range (6.5-8.5). It signifies 'slightly alkaline in nature' in all locations. Aquatic life depends on DO for its development, reproduction, and survival, and a lack of it indicates sewage pollution. The estimated values (7.258-7.828) were more than the standard limit of DO of 6.0 mg/l. The findings show that the condition of DO is at a satisfactory level and is significantly better than the standard condition. BOD must evaluate any surface and ground water contamination brought on by the discharge of domestic and industrial effluents (Eid et al. 2023). It is evident from the results that the readings (1.06-2.38) were well under the standard limit of 5 mg/l. The presence of coliform (TC) bacteria in a body of

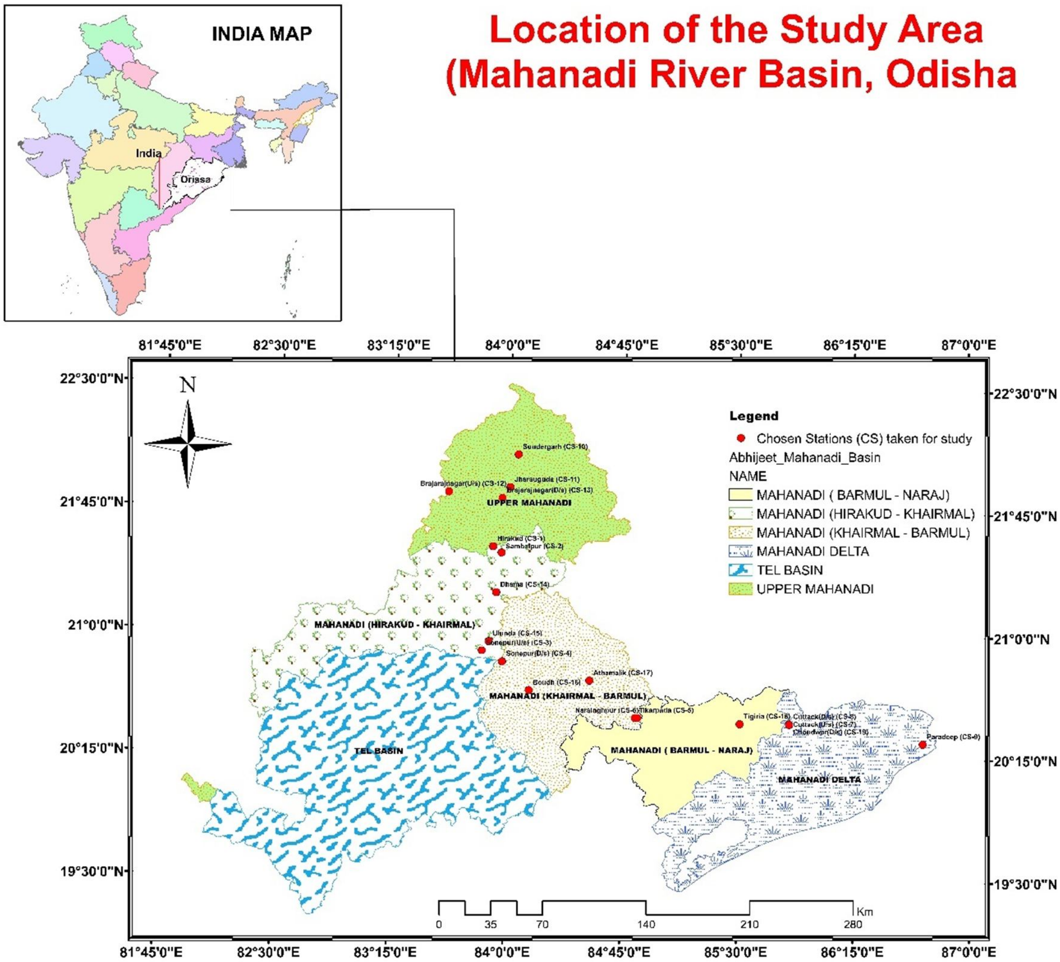

Figure 1. Location of the study area with surface water sampling points

water guarantees faecal contamination, which raises health risks and renders the water unfit for consumption (Subba Rao et al. 2020). The values in the present study lie between 1211.5-42530. Numerous non-point sources, such as cleaning, bathing, washing, and animal husbandry, may be the likely cause of the elevated coliform levels (>5000 MPN/100 ml) at Sites (CS-8, 9 & 19). Due to high TSS, less light enters the water and photosynthesis proceeds more slowly, which lowers the DO level and lessens the purity of the water (Khadr et al. 2021). However, the value (28.64-74.98) was well below the threshold of 200 mg/l as per WHO (2017), indicates for drinking and agricultural purposes. Alkalinity is the buffering capacity of water to neutralize acids which maintains a stable pH. Alkalinity in drinking water should not exceed 200 mg/l; else, the flavour will become unpleasant. The range of values (70.38–101) is completely within the limits set by the World Health Organization (WHO 2017). However, all sites contained the desirable value i.e., 200 mg/l. The concentration of COD in home and industrial wastewater from metropolitan areas is a sign of organic pollution. Because of the establishment of anaerobic conditions brought on by high levels of dissolved organic matter and the subsequent decrease of pH, high COD may be attributed to the production of organic acids. The existing values (6.80-21.86) in the study area were below the WHO recommendation of 30 mg/l and the concentration in the river was at a level not posing a health concern. Residents' waste disposal in open spaces, sewage treatment, and chemical fertilizers were the main contributors to NH_3-N contamination of surface waters. This could be a result of open defecation and filthy practises such as dirty water disseminated from local sewers and runoff from adjacent places (Tiyasha et al. 2020). The obtained range in the current work is between 0.512 and 1.940. All of the physicochemical characteristics of the water that was analysed were well below the WHO-recommended permitted limits (2 mg/l) for drinking water. Surface water can also become contaminated with free-NH_3 due to the usage of fertilisers that depend on nitrogen, such as NPK (nitrogen, phosphorus, and potassium) fertilisers, poor human and animal waste disposal practises, unlined drainage systems, and drainage lines. The recommended limit for drinking water is 2.0 mg/l (WHO 2017). However, all observations were within the prescribed limits for all sampling locations. TKN contamination in surface water is caused by leaching from agricultural land, solid waste disposal sites, or ammonia oxidation. In the present study, it ranges between 3.285-11.796 mg/l, which represents higher value than the acceptable limits of 5 mg/l. However, most of the places had significant concentrations, which pointed to anthropogenic contamination, runoff from agricultural land, and the mixing of human and animal waste. High TKN may have negative health impacts that are classified as noncarcinogenic dangers to people. High EC values indicate high water mineralization as a result of geogenic and human-caused processes (Islam Khan et al. 2022). As the EC and TDS value increases, the amount of mineral salt soluble in water increases. A very slight variation of EC was found as 137.60-7779.78 during the study period. The desirable limit considered for EC in drinking water is taken as 2250 µS/cm.(WHO 2017). Higher EC values at CS-9 suggest that the surface water contains an excess of cations and anions. The higher the EC, greater is the enrichment of salts. SAR is a crucial tool for assessing the adequacy of water quality since its increased content causes the interchange of Mg^{2+} and Ca^{2+} ions, which limits soil permeability and harms drainage systems (Jiang et al. 2020). The limit set for drinking water is 10 mg/l as per WHO (2017). The recorded values ranged from 0.401-16.49. Water with an excessive concentration of CS-9 (>10 mg/l) is frequently unsuitable for drinking and irrigation, which causes the soil's properties to deteriorate, change its structural characteristics, and become alkaline. It often noticed that intake at higher levels, it causes hypertension (high blood pressure). B^+ is very important for maintaining good health, however consuming more over the recommended quantity can have negative health effects like hypertension and nausea. It is indeed the most important nutrient component. The results revealed that readings were in the range of 0.031-0.561 mg/l. It has been noted that the content in every water sample is less than the allowed limit of 2.0 mg/l. Major health concerns like kidney stones, heart disease, and stomach difficulties could be brought on by a high TDS value. In the investigation, the recorded values ranged from 82.28-13229, indicating well within the limits (100 mg/l) except at CS-9. Higher value noticed in water can alter the taste and hardness of water. Hence, it indicates that water is highly mineralized at location CS-9. Hardness (TH) is a crucial factor in deciding whether surface water is suitable for home and industrial usage since it contributes to the hardness of the water. However, it increases the need for detergents when cleaning and some research suggests that it may contribute to heart disease. Its value ranged from 51.18 to 2195.12 and is a result of the presence of Ca^{2+} and Mg^{2+} ions in the river. The values in the present study were below the desirable threshold of 250 mg/l except CS-9. The contamination from untreated effluents and the haphazard construction of a few companies and local homes in such areas cause higher values at CS-9 (Jamei et al. 2022a). The quantify of Cl^- proportion in the ongoing study was found to be 9.645- 4904.921 mg/l. Apart from CS-9, it is substantially below the WHO-recommended limit of 250 mg/l for Cl^- in drinking water. However, sewage discharge and runoff from inorganic fertilisers from agricultural areas are its main contributory sources. Due to sewage discharge and surface runoff from contaminated areas, SO_4^{2-} can infiltrate water streams. The value of Sulphate was in a range of 4.965-375.98 mg/l in the present study. Given that the research area is heavily influenced by agriculture, an increase in sulphate content at CS-9 (>200 mg/l) may be related to runoff from agricultural activities. Leachate from closed mines, air deposition from burning fossil fuels, and industrial waste water are possible additional sources. F^- primarily found in water as a result of geological process. Human health is improved by drinking water with an allowed level of 1 mg/l of F^-. The value was found to have in between 0.256-1.0 mg/l. At every location, the concentration was acceptable, and after disinfection, the water could be consumed. NO_3^- is a representation of the hydrological, household, industrial, and agricultural waste water inputs. It is explained that 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 area as a result (Ghoderao et al. 2022). The reported readings confirmed that nitrate was in the range of 1.279-2.689 mg/l. As suggested by WHO (2017), it highlights 45 mg/l is considered as the desirable value for human consumption. At all sites, these concentrations obeyed the allowable limits. Fe^{2+} is a marker of industrial effluents, which are leftovers from the production of pigments and corrosion inhibitors, both of which may be harmful to aquatic life. The effect of Fe^{2+} on human health depends on its oxidation state. It is an essential nutrient for the human body but too much uptake can cause liver, DNA, and kidney problems. In sampling stations of the study area, concentrations (0.59-2.612) are within the threshold of drinking water limits (3 mg/l). For further analysis, the e-WQI has been used to ascertain whether the water quality is suitable for drinking. It contains all physicochemical metrics as well as the ARAS methodology's overall ranking of the sampling sites. It functions as a step up from conventional WQIs, which weight parameters based on subjective evaluation and professional opinion. In Table 1, the e-WQI values for each sample are listed.

It values varied in the range 14.55-1065.20 in the ongoing work. These readings signified that the water quality was excellent to extremely poor. The excellent category was occupied by about 84.21% of the samples, proving that surface water is suitable for drinking. The remaining samples, 10.53% and 5.26%, were in the poor or extremely poor category and are not advised for drinking. The area with the highest value, CS-9, showed substantial concentrations of EC, SAR, TDS, TH, Cl^-, SO_4^{2-}, TKN and TC. The following location provides new insight on the leaching and runoff from roadside dumps, roads, and agricultural lands. This further demonstrates how anthropogenic activities have a detrimental effect on the quality of surface water. The water quality of the river was better on the U/s side because of dilution and higher water depth. Hence, out of 19 sites, 3 sites recorded poor/ extremely poor-quality e-WQI values and this may be due to various natural phenomena and anthropogenic activities. Figure 2 shows how each water quality parameter's concentration was shown on spatial maps in ArcGIS 10.5. By displaying their aggregate rankings, the ARAS technique, on the other hand, clearly identifies the relative pollution level. Such a ranking is beneficial in assisting policy makers with both technical and non-technical backgrounds in reaching decisions that are well-informed. In this study, decision-making for choosing the best places along the river stretch with water quality that satisfied drinking standards took into account all 20 parameters. In Table 1, the sampling sites' performance rating and ARAS rankings are displayed. Additionally, Figure 3 displays the ARAS ranks' spatial variability. In compared to other places throughout the study period, the sampling point CS-9 was the most polluting, followed by CS-8 and 19. The proposed methodology, which is a dependable method based on entropy weights and applying rough set theory, results in a reliable analysis from various parameter weights. The findings show that these stations are extremely susceptible to human-induced activity (Oladipo et al. 2021). The effects of human activity on water quality outweighed the effects of natural forces (Kabir et al. 2021). Additionally, the river runs through the city's periphery, and extremely high TC and TKN readings at every location point to potential contamination from surrounding residential and agricultural operations. Water quality changes may be facilitated by the intensive use of pesticides, fertilisers, and organic additions in agricultural regions. Our findings are in line with the two methodologies, which found that changes in land cover (pastures and agriculture), particularly during the summer, are a significant cause of changes in water quality. Additionally, geological formations and soils may be linked to seasonal and spatial variations in water quality indicators, which may encourage changes in the water system in connection to water quality indicators.

TABLE I. E-WQI VALUES, SCORE OF PERFORMANCE AND ITS ARAS RANKS IN ALL SAMPLING LOCATIONS OF THE STUDY AREA

Sample No	e-WQI	Water type	ARAS	Rank
CS-1	15.69	Excellent	0.025	16
CS-2	18.4	Excellent	0.03	9
CS-3	16.21	Excellent	0.025	15
CS-4	19.88	Excellent	0.031	6
CS-5	18.58	Excellent	0.029	11
CS-6	19.47	Excellent	0.029	10
CS-7	17.61	Excellent	0.028	12
CS-8	196	Poor	0.074	2
CS-9	1065.2	Extremely Poor	0.959	1
CS-10	14.97	Excellent	0.025	17
CS-11	15.08	Excellent	0.024	19
CS-12	14.55	Excellent	0.025	18
CS-13	16.93	Excellent	0.027	13
CS-14	19.98	Excellent	0.03	7
CS-15	16.32	Excellent	0.027	14
CS-16	18.35	Excellent	0.031	4
CS-17	19.45	Excellent	0.03	8
CS-18	17.91	Excellent	0.031	5
CS-19	152	Poor	0.046	3

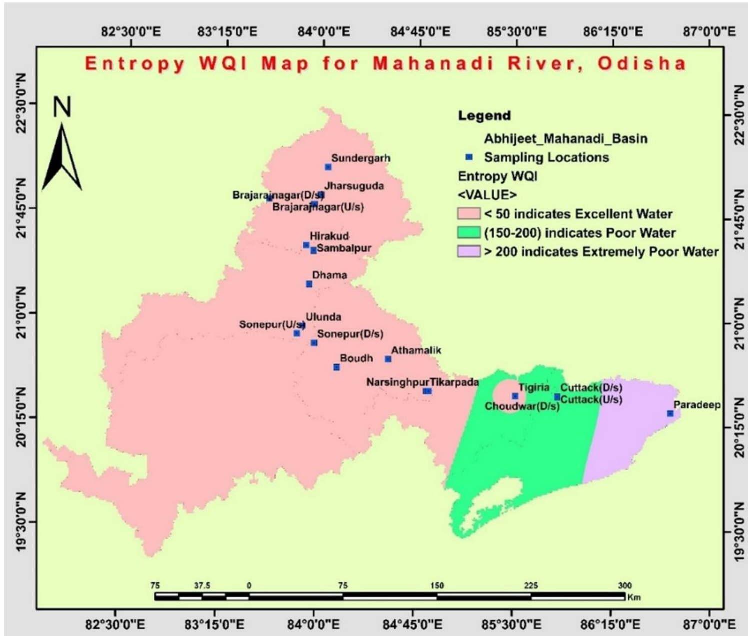

Figure 2. Spatial distribution map of e-WQI of all locations

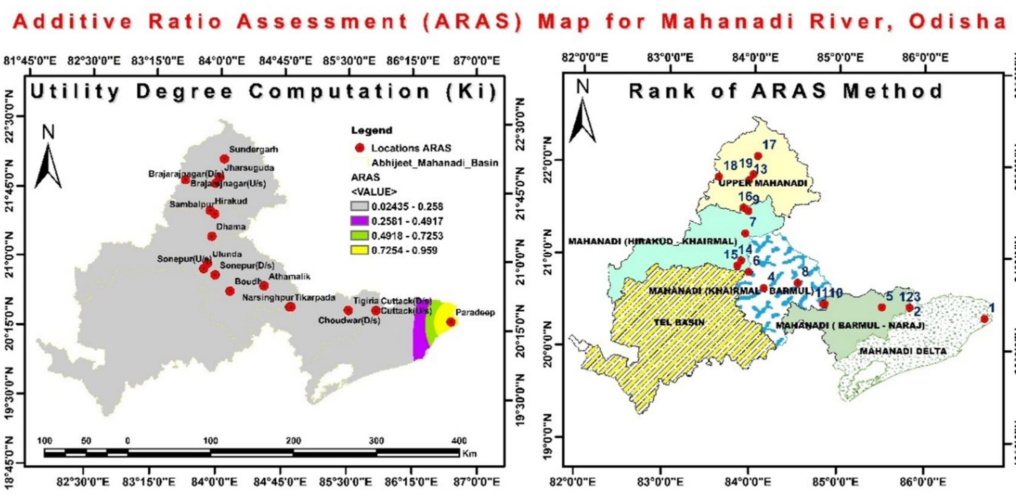

Figure 3. Spatial distribution map of ARAS methodology adopted for all locations

VI. Conclusions

The following is a summary of the results.

The present study investigated surface water quality using entropy-Water Quality Index (e-WQI) and the MCDM method namely Additive Ratio Assessment (ARAS). From this study, the regions with surface water quality issue were identified using the integrated approach. pH of all the samples shows a mild-alkaline condition in surface water. The values of TC and TKN are found to be above than the acceptable limits, as given by WHO guidelines. The classification of e-WQI suggests three categories “excellent”, “poor” and “extremely poor”, which represents 84.21%, 10.53% and 5.26% of the total samples. The spatial map of e-WQI illustrates that locations CS-8, 9 and 19 falls under poor/extremely poor zone, thus, unsuitable for drinking purpose. The cause might be due to large-scale farming and intensive industrial activities. These areas are also affected by domestic sewage discharge, garbage disposal irrational use of pesticides, and landfill activities. The results of

ARAS classification match those of the entropy method's water quality calculations, demonstrating the accuracy and usefulness of these two methods. The accuracy of the entropy method computation can be increased by using ranks provided by ARAS. The water quality is also assessed using the entropy approach based on weights, and the data are then further calculated and analysed. The ARAS results show that the water quality at CS-9 is regarded as the most polluted location because it is impacted by anthropogenic activities such as over-extraction of surface water in the research region as well as agricultural, industrial, and industrial activities. Implementing safe working methods, such as sewage treatment facilities and safety precautions during drinking, irrigation, and industry operations, is strongly advised without having an adverse impact on the environment's resources. All of these indicate to the model's suitability for evaluating the water quality of several sampling points and its positive outcomes.

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