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A Comparative Analysis of Drinking Water Quality at Railway Stations in Tripura Using TOPSIS, VIKOR, and a PCA-Based Robust Ranking Method

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ABSTRACT: Effective ranking of alternatives in multi-criteria decision making (MCDM) problems is vital across disciplines such as engineering, economics, and the social sciences. This study employs two well-established MCDM techniques such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), to assess the drinking water quality at 27 railway stations in Tripura, India. A total of 13 water quality parameters were initially considered, however Principal Component Analysis (PCA) revealed that only 5 parameters were statistically significant. These 5 key parameters were subsequently used for ranking the railway stations through both TOPSIS and VIKOR methods. To evaluate the consistency between the two ranking methods, Spearman's rank correlation coefficient was calculated and found not to be close to one, indicating a lack of high correlation. In response to this discrepancy, a new approach named Robust Ranking Method (RRM) has been proposed here. The RRM integrates the 5 significant parameters using a linear combination, with PCA-derived eigenvalues as weights, to provide a more stable and interpretable ranking of drinking water quality across the stations. The proposed methodology offers a novel and reliable framework for environmental quality assessment in multi-criteria contexts.

Key Words: Spatial statistics, transport problems, Sustainable Development Goal (SDG)s, Multi-Criteria-Decision-Making Problems.

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1. Introduction

Water quality plays an essential role in ensuring public health, particularly in high-footfall and sensitive areas such as railway stations where the risk of waterborne diseases is significantly elevated [1]. In India, and more specifically in northeastern states like Tripura, water quality management faces unique challenges due to infrastructural limitations, environmental heterogeneity, and inconsistent monitoring mechanisms [2,3]. The provision of safe and potable water in such public spaces is not only a matter of health and hygiene but also of infrastructural accountability and environmental justice. Assessing the

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quality of drinking water requires an integrated analysis of various physicochemical parameters, such as pH, total dissolved solids (TDS), turbidity, nitrates, fluoride, and heavy metals, each contributing differently to overall water safety [4]. Traditional assessment methods often fall short in capturing the multifaceted nature of water quality data, especially when parameters are interrelated or exhibit multicollinearity [5]. In this context, Multi-Criteria Decision Making (MCDM) techniques offer a promising solution by enabling systematic and data-driven evaluation across multiple conflicting criteria. Widely used MCDM methods like TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) have been successfully applied in environmental studies, hydrological planning, and urban infrastructure management due to their logical frameworks and adaptability [6,7,8]. While TOPSIS emphasizes proximity to an ideal solution [9], VIKOR balances group utility with individual regret, making it suitable for compromise-based decision making [10]. However, several studies have raised concerns regarding the sensitivity of MCDM results to input weights and data variability, thereby questioning their robustness in complex real-world scenarios [11,12]. This has led to growing interest in developing more statistically grounded and stable decision-support tools. Spatial statistical optimization and the integration of eigenvalue-based parameter weighting have been suggested as potential solutions to overcome the limitations of conventional methods [13,14,15]. In response to this methodological gap, the present study aims to assess and rank the quality of drinking water at selected railway stations in Tripura using established MCDM approaches (TOPSIS and VIKOR) alongside a newly developed Robust Ranking Method (RRM). RRM introduces an eigenvalue-weighted ranking framework designed to offer more stable, adaptable, and statistically consistent outcomes. By combining spatial analysis, statistical weighting, and decision modeling, this study not only contributes to the domain of public infrastructure assessment but also offers a replicable methodological framework for similar applications in water management and environmental monitoring across India [16,17]

2. Study Area

This study evaluates the drinking water quality across 27 railway stations located in the state of Tripura, one of India's northeastern states, using 13 specific water quality parameters. Tripura encompasses a geographical area of approximately 10,486 square kilometers and shares an 856 km international boundary with Bangladesh on its north, west, and southern sides. To its northeast and east, it is bordered by the Indian states of Assam (53 km) and Mizoram (109 km), respectively [18]. Tripura's terrain is predominantly hilly, with around 60% of the land categorized as elevated terrain comprising valleys and ridges—locally referred to as tilla and lunga. The remaining 40% consists of uneven plains, often interspersed with undulating hillocks and low hills rising 30–60 meters, mostly covered by dense vegetation [19]. The state features six prominent anticlinal hill ranges: Baramura, Atharamura, Longtharai, Shakhan, Jampui, and Deotamura. The railway network in Tripura traverses through major hill systems, including Longtharai (515 m), Atharamura (481 m), and Baramura (249 m), forming a critical link from the northern to the southern districts. Numerous rivers and streams emerge from these ranges, contributing to Tripura's fluvial landscape. Prominent rivers include the Longai (98 km), Deo (98 km), Manu (167 km), Dhalai (117 km), Khowai (70 km), Haora (53 km), Bijoy (26 km), Gomati, Muhuri (64 km), and Feni, among others. The state's transport infrastructure, especially roads, faces severe disruption during the monsoon season due to frequent landslides in the hilly areas [20]. Consequently, the railway has emerged as the most reliable mode of transportation, especially since the completion of gauge conversion in 2016, which improved connectivity and freight mobility [21]. Since 2016, the railway network in Tripura has played a crucial role in facilitating freight transportation [22]. Tripura has around 264 km of railway track stretching from Churaibari Railway Station (CBZ) in the north (24°26′ N, 92°14′ E) to Sabroom Railway Station (SBRM) in the south (23°00′ N, 91°41′ E), encompassing 25 intermediate stations. These include:

- Nadiapur [NPU] (24°23′ N, 92°12′ E)
- Dharmanagar [DMR] (24°22′ N, 92°10′ E)
- Panisagar [PASG] (24°16′ N, 92°09′ E)
- Pencharthal [PEC] (24°11′ N, 92°06′ E)

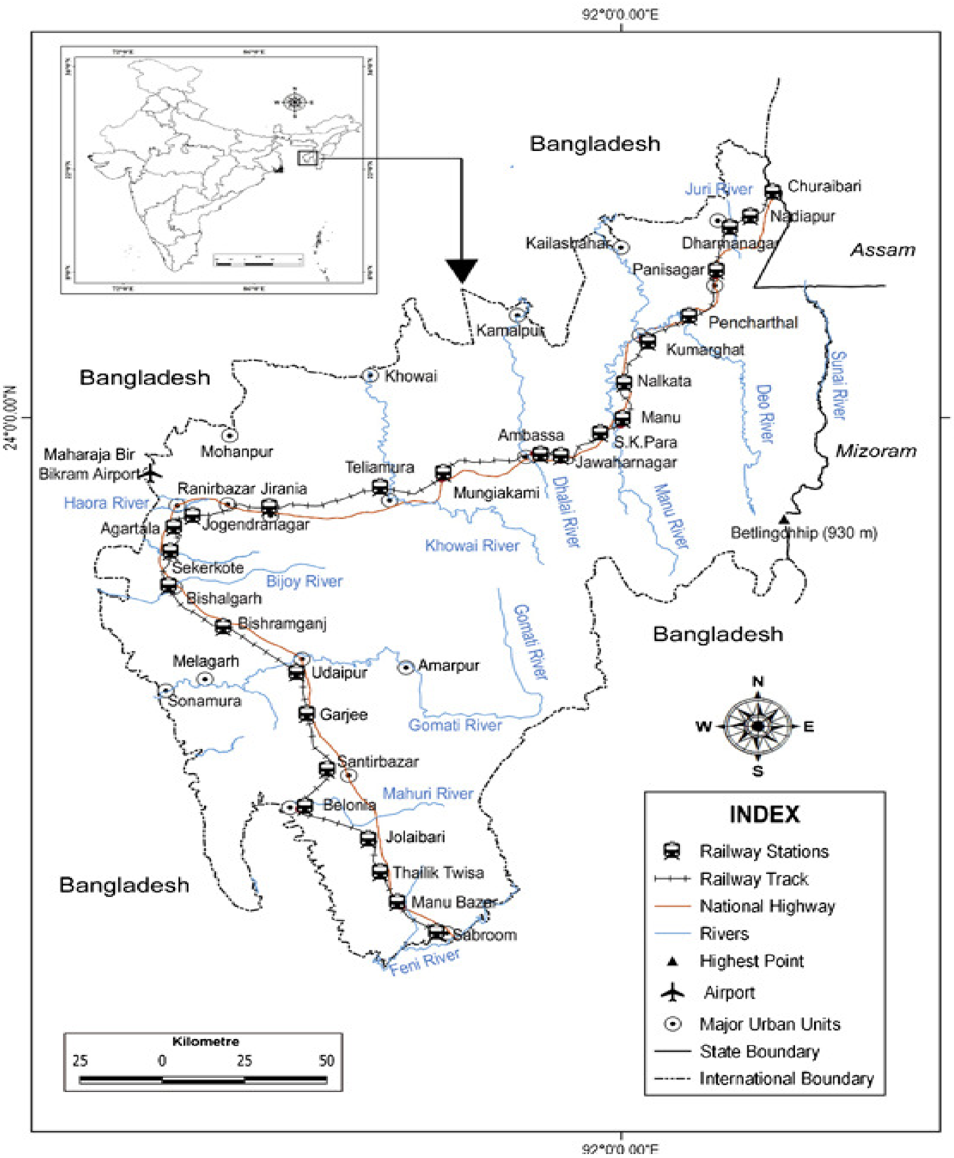

Figure 1 : Location map of the study area (source: data extracted from Handheld GPS receiver, Google Earth Pro and SAS Planet v. 210,805)

- Kumarghat [KUGT] (24°09′ N, 92°02′ E)
- Nalkata [NLKT] (24°03′ N, 92°00′ E)
- Manu [MANU] (23°59′N, 91°59′E)
- S.K. Para [SKAP] (23°58′N, 91°58′E)
- Jawaharnagar [JWNR] (23°55′N, 91°54′E)
- Ambassa [ABSA] (23°55′N, 91°51′E)
- Mungiakami [MGKM] (23°53′N, 91°42′E)
- Teliamura [TLMR] (23°51′N, 91°37′E)
- Jirania [JRNA] (23°49′N, 91°25′E)

- Jogendranagar [JGNR] (23°44′N, 91°18′E)
- Agartala [AGTL] (23°47′N, 91°16′E)
- Sekerkote [SKKE] (23°44′N, 91°16′E)
- Bishalgarh [BLGH] (23°40′N, 91°16′E)
- Bishramganj [BHRM] (23°35′N, 91°21′E)
- Udaipur [UDPU] (23°30′N, 91°28′E)
- Garjee [JRJE] (23°25′N, 91°29′E)
- Santirbazar [STRB] (23°19′N, 91°31′E)
- Belonia [BENA] (23°14′N, 91°29′E)
- Jolaibari [JLBRI] (23°11′N, 91°35′E)
- Thailik Twisa [THTW] (23°07′N, 91°36′E)
- Manu Bazar [MUBR] (23°03′N, 91°38′E) (Fig. 1)

3. Methodology

3.1. Data Description

The dataset comprises water quality measurements collected from 27 railway stations in the state of Tripura, India, to evaluate the suitability of drinking water in public transit environments. A total of 13 physicochemical parameters were initially recorded for each station, selected based on their environmental relevance, public health importance, and regulatory importance as defined by the Bureau of Indian Standards (BIS) and the World Health Organization (WHO).

Principal Component Analysis (PCA) was applied as a dimension reduction technique to identify the most influential variables that contribute to the overall variance in water quality.

Number	Variables	Eigenvalue	%	Plot	Cum. Per cent	ChiSquare	P-Value
1	Chloride	2.9834	22.949		22.949	133.668	<.0001*
2	E. Coli	2.1315	16.396		39.345	105.833	0.0036*
3	Turbidity	1.7263	13.280		52.625	88.809	0.0116*
4	Fluoride	1.4950	11.500		64.125	72.431	0.0336*
5	Iron	1.0899	8.384		72.509	59.637	0.0540
6	Sulphate	0.8115	6.242		78.751	50.269	0.0492*
7	Arsenic	0.7408	5.698		84.449	41.055	0.0491*
8	Total Hardness	0.6218	4.783		89.232	33.107	0.0423*
9	Total Coliform	0.5217	4.013		93.246	27.563	0.0210*
10	Nitrate	0.3744	2.880		96.126	20.989	0.0166*
11	TDS	0.3634	2.795		98.921	13.986	0.0193*
12	pH	0.0908	0.699		99.620	1.346	0.4948
13	Alkalinity	0.0495	0.380		100.000	0.000	.

Figure 2 : Source: Computed by the authors, 2025

Through PCA, the eigenvalues of the covariance matrix were calculated and the top five parameters that explain most of the cumulative variance were selected for further analysis. These five most statistically significant parameters, retained based on their contributions to eigenvalues and factor loadings, were: (i) Chloride (mg / L), (ii) Ecoli, (iii) Turbidity (NTU), (iv) Fluoride (mg / L) and (v) Iron (Fig. 2). These variables served as input criteria for the application of multi-criterion decision making (MCDM) methods: TOPSIS, VIKOR and the newly developed Robust Ranking Method (RRM). All parameter values were standardized to eliminate unit disparities, ensuring valid cross-criteria comparisons. This dimensional reduction ensures methodological efficiency, reduces noise and redundancy, and enhances the robustness and interpretability of the ranking results.

3.2. Application of Traditional MCDM Methods

To rank the 27 railway stations based on their water quality, two established Multi-Criteria Decision Making (MCDM) techniques were applied: TOPSIS and VIKOR. These methods process the normalized performance values and weights of each criterion to produce a composite ranking of alternatives.

3.2.1. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). TOPSIS, proposed by [6], identifies the alternative closest to the ideal solution and farthest from the negative-ideal solution by calculating the geometric (Euclidean) distances. Let:

- $i \in \{1, 2, \ldots, 27\}$ denote the index for railway stations (alternatives),
- $j \in \{1, 2, \ldots, 5\}$ denote the index for selected water quality parameters (criteria).

Step 1: Normalization of the Decision Matrix Let x_{ij} denote the value of the j^{th} criterion for the i^{th} alternative. Hence the respective normalized value of the j^{th} criterion for the i^{th} alternative, r_{ij} is computed as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{3.1}$$

Where:

- x_{ij}: value of criterion j for alternative i
- r_{ij}: normalized value
- $n = 27$: total number of alternatives

Step 2: Weighted Normalized Decision Matrix

$$v_{ij} = w_j \cdot r_{ij} \tag{3.2}$$

where w_j is the weight assigned to the j^{th} criterion.

Step 3: Determine Ideal (A^+) and Negative-Ideal (A^-) Solutions

$$A^+ = \{\max(v_{ij}) \mid j \in J_b; \min(v_{ij}) \mid j \in J_c\} \tag{3.3}$$

$$A^- = \{\min(v_{ij}) \mid j \in J_b; \max(v_{ij}) \mid j \in J_c\} \tag{3.4}$$

where J_b and J_c represent benefit and cost criteria, respectively.

Step 4: Calculate Separation Measures

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - A_j^+)^2} \tag{3.5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - A_j^-)^2} \tag{3.6}$$

Step 5: Calculate Closeness Coefficient

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{3.7}$$

Alternatives are ranked based on the descending order of CC_i, where a higher value indicates better performance.

3.2.2. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje). Another method named VIKOR, developed by [7], seeks a compromise solution by maximizing group utility and minimizing individual regret.

Step 1: Determine Best and Worst Values

$$f_j^* = \max_i x_{ij}, \quad f_j^- = \min_i x_{ij} \tag{3.8}$$

Step 2: Compute Utility and Regret Measures

$$S_i = \sum_{j=1}^{m} w_j \cdot \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \tag{3.9}$$

$$R_i = \max_j \left[w_j \cdot \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \right] \tag{3.10}$$

Step 3: Compute the VIKOR Index

$$Q_i = v \cdot \frac{S_i - S^*}{S^- - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*} \tag{3.11}$$

Where:

- $v = 0.5$ (typically)
- $S^* = \min S_i$, $S^- = \max S_i$
- $R^* = \min R_i$, $R^- = \max R_i$

Alternatives are ranked in ascending order of Q_i.

3.2.3. Consistency Check using Spearman's Rank Correlation. To assess the agreement between the rankings from TOPSIS and VIKOR, the Spearman's rank correlation coefficient ρ is calculated as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{3.12}$$

where d_i is the difference between the ranks of station i in the two methods, and $n = 27$ is the total number of stations. The range of ρ lies between $[-1, +1]$, where -1 indicates perfect negative correlation between two variables and $+1$ indicates perfect positive correlation and correlation value closes to 0 assumes as no-correlation. Degree of correlation from zero to low to moderate and high are based on respective value and dimension depends of sign of respective correlation value.

3.3. Development of Robust Ranking Method (RRM)

To assess the potability of water at the 27 railway stations in Tripura, a novel approach called the Robust Ranking Method (RRM) has been proposed. This method aims to overcome the limitations of subjectivity in traditional MCDM techniques by integrating statistical reliability through Principal Component Analysis (PCA). RRM provides a linear combination of the five most statistically significant parameters, where the eigenvalues obtained from PCA are taken as the coefficients (weights) of the respective parameters.

Step 1: Compute Covariance Matrix Let X be the standardized data matrix of size $n \times m$ (where $n = 27$, $m = 13$). The covariance matrix is:

$$C = \frac{1}{n-1} X^\top X \tag{3.13}$$

Step 2: Eigenvalue Decomposition

$$C = PDP^{-1} \tag{3.14}$$

where D is a diagonal matrix of eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_m$ and P contains the corresponding eigenvectors.

Step 3: Select Top $k = 5$ Parameters Choose the five parameters with the highest eigenvalues.

Step 4: Eigenvalue-Based Weights The eigenvalues obtained from PCA are taken as the coefficients (weights) of the respective parameters.

Step 5: Compute Composite Index Let r_{ij} be the normalized value of parameter j for station i. The robust score R_i is:

$$R_i = \sum_{j=1}^{5} w_j \cdot r_{ij} \tag{3.15}$$

Step 6: Final Ranking Stations are ranked in descending order of R_i, with higher scores indicating better water quality performance.

4. Results and Discussion

4.1. Comparative Analysis of Ranking Methods

To assess the drinking water quality across 27 railway stations in Tripura, three Multi-Criteria Decision Making (MCDM) methods: TOPSIS, VIKOR, and the newly proposed Robust Ranking Method (RRM) were applied. The results revealed substantial differences in the station rankings produced by each method. TOPSIS, determines the closeness of each alternative to the ideal solution. Conversely, VIKOR, employs a compromise-based strategy, considering both the best and worst performances to identify a middle-ground solution. Though a Spearman's rank correlation, $\rho = 0.7814408$ underscores the positive relation between the rankings produced by the two approaches, but the experimenter may confuse to decide about the actual ranking positions of respective stations while seeing in the rank suggested by these two different approaches. Station Belonia got first rank regarding the VIKOR method but obtained the 9th position considering TOPSIS. On the other hand, Jogendranagar was selected for the third position regarding VIKOR but the 15th according to TOPSIS. The preference of the station to improve the water quality will be affected according to the choice of the method.

To avoid such disparity, the Robust Ranking Method (RRM) offers an alternative approach by incorporating eigenvalue-weighted linear combinations of the five most statistically significant water quality parameters. This approach draws from principal component analysis (PCA) logic, capturing the underlying structure of multivariate data. Unlike the stark divergence between TOPSIS and VIKOR, RRM achieved high positive correlations with both: 0.9774115 with TOPSIS and 0.8125763 with VIKOR. Both correlation values are higher than the TOPSIS and VIKOR, as reported earlier. This suggests that RRM could function as a bridge between ideal-based and compromise-based methods, offering a more balanced perspective in decision making.

4.2. Ranking Outcomes and Observations

The detailed rankings of 27 stations under the three methods are presented below.

Table 1: Rank of all the station through TOPSIS method

Sl No	Station	Score	Rank	Sl No	Station	Score	Rank
1	Churaibari	0.8825	6	15	Jogendranagar	0.8975	3
2	Nadiapur	0.6940	19	16	Agartala	0.8788	7
3	Dharmanagar	0.8513	10	17	Sekerkote	0.9428	2
4	Panisagar	0.5824	26	18	Bishalgarh	0.8143	14
5	Pencharthal	0.7616	17	19	Bishramganj	0.6043	25
6	Kumarghat	0.8968	4	20	Udaipur	0.8199	13
7	Nalkata	0.6787	21	21	Garjee	0.8738	8
8	Manu	0.6493	22	22	Santirbazar	0.6409	24
9	S.K. Para	0.6795	20	23	Belonia	0.8550	9
10	Jawaharnagar	0.8331	12	24	Jolaibari	0.4103	27
11	Ambassa	0.8512	11	25	Thailik Twisa	0.7733	16
12	Mungiakami	0.8945	5	26	Manu Bazar	0.7434	18
13	Teliamura	0.9511	1	27	Sabroom	0.6422	23
14	Jirania	0.8019	15				

Table 2: Rank of all the station through VIKOR method

Sl No	Station	Score	Rank	Sl No	Station	Score	Rank
1	Churaibari	0.5316	18	15	Jogendranagar	0.4704	15
2	Nadiapur	0.5468	19	16	Agartala	0.2650	9
3	Dharmanagar	0.1954	7	17	Sekerkote	0.1172	3
4	Panisagar	0.7216	21	18	Bishalgarh	0.2900	10
5	Pencharthal	0.7584	23	19	Bishramganj	0.4794	16
6	Kumarghat	0.3890	11	20	Udaipur	0.1360	4
7	Nalkata	0.8438	25	21	Garjee	0.1502	6
8	Manu	0.8067	24	22	Santirbazar	0.8965	26
9	S.K. Para	0.5043	17	23	Belonia	0.0271	1
10	Jawaharnagar	0.3932	12	24	Jolaibari	0.9675	27
11	Ambassa	0.1967	8	25	Thailik Twisa	0.3998	13
12	Mungiakami	0.1395	5	26	Manu Bazar	0.7008	20
13	Teliamura	0.0512	2	27	Sabroom	0.7523	22
14	Jirania	0.4441	14				

4.3. Discussion

The study's comparative approach highlights the inconsistencies inherent in relying on a single MCDM technique. The RRM offers a statistically rigorous and interpretable alternative that accommodates the strengths of both traditional methods. It can be particularly useful in public infrastructure planning, where data heterogeneity and stakeholder conflict are common. RRM's alignment with principal component analysis principles also makes it compatible with other multivariate techniques. Its flexibility is particularly useful in environmental applications where parameter distributions are non-normal and often interrelated. This method is scalable and adaptable. Future applications could include infrastructure evaluation, climate impact assessment, and health facility planning, where multiple criteria and stakeholder interests converge.

The heatmap provides a visual comparison of the rankings assigned to 27 railway stations in Tripura using three multi-criteria decision making (MCDM) methods: TOPSIS, VIKOR, and a Proposed Index. Each cell displays the rank of a station under a given method, with lighter shades representing better ranks (closer to 1) and darker shades indicating poorer performance. This color-coded representation helps identify stations that consistently perform well across methods, as well as those with significant

Table 3: Rank of all the station through RRM

Sl No	Station	Score	Rank	Sl No	Station	Score	Rank
1	Churaibari	1.031725364	7	15	Jogendranagar	0.986801636	5
2	Nadiapur	1.801118826	22	16	Agartala	1.021792306	6
3	Dharmanagar	1.09601012	10	17	Sekerkote	0.750674816	2
4	Panisagar	2.187765572	26	18	Bishalgarh	1.322307683	15
5	Pencharthal	1.373028141	17	19	Bishramganj	1.72257175	19
6	Kumarghat	0.979834214	4	20	Udaipur	1.257214013	13
7	Nalkata	1.725014729	20	21	Garjee	1.062716967	9
8	Manu	1.929496339	24	22	Santirbazar	1.883222555	23
9	S.K. Para	1.768952575	21	23	Belonia	1.031863097	8
10	Jawaharnagar	1.25018212	12	24	Jolaibari	2.602960547	27
11	Ambassa	1.182072445	11	25	Thailik Twisa	1.266475683	14
12	Mungiakami	0.925497022	3	26	Manu Bazar	1.495447079	18
13	Teliamura	0.705209119	1	27	Sabroom	1.999518953	25
14	Jirania	1.332757166	16				

rank variation. Overall, the heatmap highlights both the convergence and divergence in station rankings, offering insights into the relative strengths and weaknesses of each evaluation approach (Fig. 3).

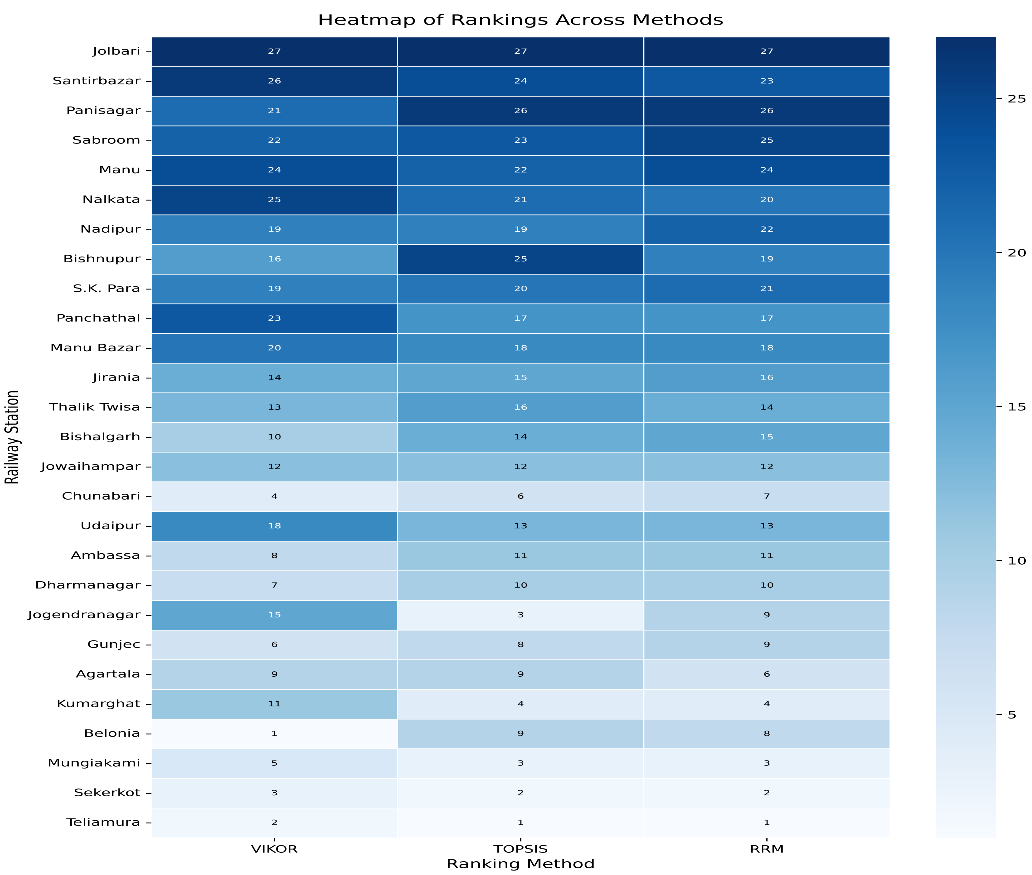

Figure 3 : Heatmap showing the rank positions of 27 railway stations in Tripura across three MCDM methods — TOPSIS, VIKOR, and Proposed Index.

5. Conclusion

This study presents a comparative framework for evaluating drinking water quality at railway stations in Tripura using three decision making techniques: TOPSIS, VIKOR, and the proposed Robust Ranking Method (RRM). The findings confirm that conventional methods may yield inconsistent results due to their differing optimization principles—ideal proximity in TOPSIS and compromise in VIKOR. The RRM, by leveraging principal component analysis to define weights based on statistical significance, demonstrates greater balance and interpretability. Its high positive correlation with both TOPSIS and VIKOR validates its role as a reconciling methodology. More importantly, RRM's compatibility with multivariate techniques makes it a scalable tool for various domains.

As public infrastructure decisions become increasingly complex and data-rich, there is a growing need for methodologies that are statistically grounded, transparent, and adaptable. The RRM addresses this need effectively and opens up future applications in fields such as environmental monitoring, urban planning, health infrastructure, and climate impact assessment.

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