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Revolutionizing Groundwater Suitability with AI-Driven Spatial Decision Support—A Remote Sensing and GIS Approach for Visakhapatnam District, Andhra Pradesh, India

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Abstract

This study presents an AI-driven Spatial Decision Support System (SDSS) aimed at transforming groundwater suitability assessments for domestic and irrigation uses in Visakhapatnam District, Andhra Pradesh, India. By employing advanced remote sensing, GIS, and machine learning techniques, groundwater quality data from 50 monitoring wells, sourced from the Central Ground Water Board (CGWB), was meticulously analysed. Key parameters, including pH, electrical conductivity, total dissolved solids, and major ion concentrations, were evaluated against World Health Organization (WHO) standards to determine domestic suitability. For irrigation, advanced metrics such as Sodium Adsorption Ratio (SAR), Kelly's Ratio, Residual Sodium Carbonate (RSC), and percentage sodium (% Na) were utilized to assess water quality. The integration of GIS for spatial mapping and AI models for predictive analytics allows for a comprehensive visualization of groundwater quality distribution across the district. Additionally, the irrigation water quality was evaluated using the USA Salinity Laboratory diagram, providing essential insights for effective agricultural water management. This innovative SDSS framework promises to significantly enhance groundwater resource management, fostering sustainable practices for both domestic use and agriculture in the region.

Keywords

Groundwater Suitability, Geospatial Analysis, Geospatial Modeling of Water

Quality, Spatial Decision Support System, Remote Sensing, Machine Learning, Visakhapatnam District

1. Introduction

Water is a fundamental natural resource essential for sustaining life, promoting human health, and driving economic development. It plays a critical role in food security, poverty reduction, and maintaining ecological balance [1]. However, the quality of water resources worldwide has been deteriorating due to both natural processes and human activities [2]. Groundwater, a major source of water for domestic, agricultural, and industrial purposes, faces significant threats from contamination, over-exploitation, and pollution [3].

In India, groundwater quality has declined due to several factors, including over-extraction without adequate recharge, excessive use of chemicals in agriculture, and the percolation of pollutants such as pesticides and fertilizers into subsurface water tables [4]. Industrial and domestic effluents, often untreated, further exacerbate the problem, leading to contamination and the loss of safe drinking water [5]. This presents a critical challenge, as access to clean and safe drinking water is a fundamental human right and essential for public health and development [6].

Particularly, Visakhapatnam District in Andhra Pradesh faces growing concerns over the suitability of its groundwater for domestic and irrigation purposes. The region has witnessed the effects of both natural geological factors and anthropogenic influences on groundwater quality [7]. The hydrochemical properties of water, including pH, electrical conductivity, and the concentration of major ions such as Ca^{2+}, Mg^{2+}, Na^{+}, and HCO_3^-, are crucial in determining its usability for domestic consumption and agricultural irrigation [8]. Excessive levels of dissolved salts can lead to salinity issues, which reduce soil permeability and adversely affect crop yields [9].

To address these challenges, advanced technologies such as remote sensing, Geographic Information Systems (GIS), and machine learning are increasingly being utilized to assess groundwater suitability [10]. These technologies enable the spatial mapping of groundwater quality and help in the development of data-driven models for decision-making in water resource management [11]. This study leverages an AI-driven Spatial Decision Support System (SDSS) to revolutionize groundwater quality analysis in Visakhapatnam District. By integrating remote sensing, GIS and machine learning, the study aims to provide a comprehensive evaluation of groundwater suitability for both domestic and irrigation purposes, ensuring sustainable water resource management for the region's future [12] [13]. While previous studies have successfully utilized AI/ML for water quality classification [14] and predictive modeling [15], this study pioneers the integration of AI-driven Spatial Decision Support Systems (SDS) to simultaneously analyze multi-parameter datasets, predict future scenarios and map spatial variations. This holistic approach not only enhances accuracy but also provides actionable insights for targeted remediation efforts in resource-limited settings.

2. Study Area

Visakhapatnam District (**Figure 1**), located in the southeastern part of India, serves as the focus of this study due to its significant reliance on groundwater for domestic, irrigation, and industrial purposes. The district encompasses an area of 11,343 km^2 and experiences an average annual rainfall of 1202 mm, which plays a crucial role in recharging groundwater resources. The diverse geomorphology of the region includes structural hills, pediplains and alluvial plains, all of which contribute to its hydrological dynamics. Major rivers such as the Machkund, Tandava, Varaha, Sarada, and Gosthani further influence the groundwater system, although large-scale groundwater extraction remains the primary method for meeting water demands.

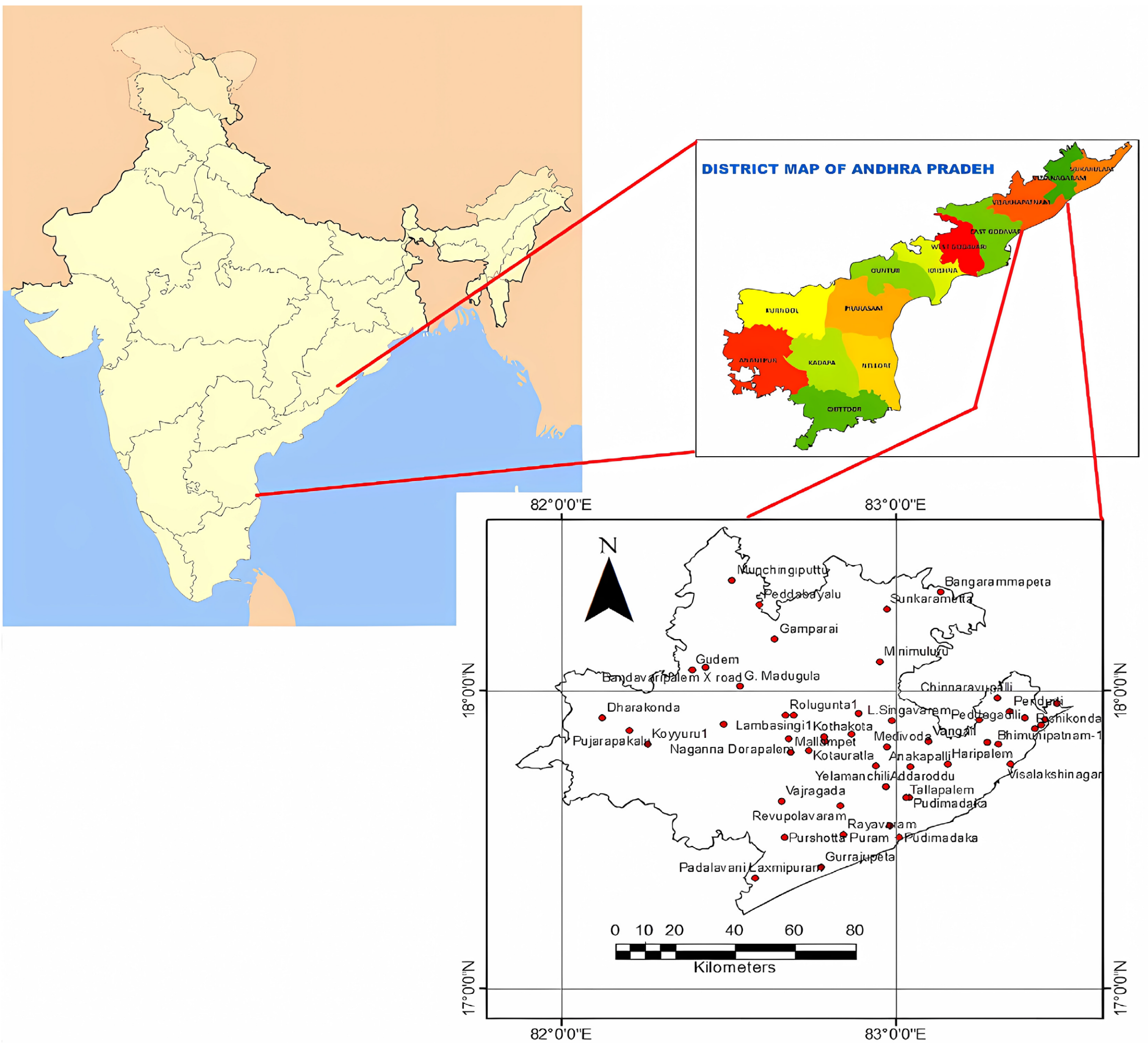

Figure 1. Location map of Visakhapatnam District, illustrating sample locations.

The total irrigated area in the district is approximately 113,246 ha, with surface water accounting for 58,521 ha, groundwater for 29,369 ha, and other sources for 25,356 ha. This highlights the significant dependence on groundwater for agricultural activities. The predominant soil types are red sandy loam and clayey soils, which affect water retention and suitability for various crops. Additionally, the geology of the area consists of formations ranging from ancient Archean to more recent sediments, including khondalite and alluvium, influencing groundwater quality and availability.

3. Data and Software

The groundwater quality data for this study was sourced from 63 exploratory wells located throughout the Visakhapatnam District. This data was obtained from the Central Ground Water Board (CGWB), Visakhapatnam. The collection mechanism involved systematic sampling procedures to ensure the accuracy and reliability of the water quality parameters, which include pH, electrical conductivity, total dissolved solids, and major ion concentrations (**Table 1**).

Table 1. Physiochemical properties of groundwater in study area.

SI. No.	Well No.	pH	EC in m	TH	CI	NO3	F	Alkalinity	TDS	Uranium
1	29	8	150	53	3	0	0.08	60	80	0.45
2	32	7.9	110	32	5	3	0.05	30	54	1.11
3	31	7.6	560	201	112	102	0.05	30	335	0.99
4	19	6.9	110	40	9	5	0.01	40	67	2.3
5	20	6.6	342	124	20	25	0.08	120	200	1.19
6	22	7.8	1584	238	37	34	4.39	600	909	3.16
7	25	7.6	211	65	10	6	0.1	60	92	1.36
8	26	7.3	462	135	46	13	0.03	120	233	0.86
9	27	7.4	225	100	3	1	0.23	110	128	1.5
10	33	7.9	2051	704	222	154	1.34	470	1209	20.3
11	37	6	116	36	2	3	0.1	40	51	0
12	38	7	170	58	17	15	0.04	40	99	0
13	41	7.5	122	36	2	11	0.15	40	63	0
14	34	8.7	133	30	7	3	0.05	30	54	1.27
15	42	7.1	260	84	25	49	0.14	50	160	0
16	62	7.9	1416	438	176	106	0.58	230	753	9.53
17	63	8	726	161	40	30	0.47	230	406	1.58
18	46	7.1	2655	695	406	131	0.39	450	1463	16.54
19	47	7.2	2130	704	220	44	0.46	500	1140	14.5
20	49	7.6	1290	233	189	55	0.29	220	759	8
21	45	7	690	232	31	3	0.65	280	376	3.56

Continued

22	60	7.7	668	165	38	3	1.48	210	314	2.06
23	52	7.7	1016	318	56	15	0.37	380	549	10.6
24	44	7	945	318	66	66	0.56	320	572	4.9
25	59	7.6	750	238	39	4	0.62	250	350	3.17
26	53	7.7	1130	172	100	27	0.16	350	680	4.62
27	58	7.7	3740	341	666	17	2.54	830	2239	38.87
28	64	7.1	560	196	11	0	0.45	270	328	0
29	48	7.5	1943	438	230	90	0.05	420	1145	8.61
30	54	7.5	1833	533	268	22	0.71	350	956	8.46
31	65	7.3	65	27	4	10	0.05	20	43	0
32	43	6.8	1245	376	84	17	0.64	420	693	8.3
33	55	7	1090	406	69	58	0.39	350	597	2.42
34	61	8	1495	272	139	40	1.31	470	878	9.05
35	50	8	176	19	34	0	0.02	30	98	1.04
36	56	7.2	2001	469	360	42	0.78	400	1151	2.61
37	57	7.3	1344	323	108	28	1.04	380	715	5.1
38	66	6.9	1245	365	126	85	0.33	260	650	2
39	51	7.5	900	188	83	3	0.29	320	550	3.15
40	820	7.4	1235	448	111	80	0.38	260	703	6.05
41	821	7.7	1150	270	136	22	0.51	290	683	3.1
42	815	7.3	800	246	106	8	0.36	220	442	5.9
43	822	7.7	942	276	84	25	0.33	150	485	3.72
44	823	7.2	805	202	61	62	0.95	180	413	2.22
45	816	7.2	2130	301	307	91	0.38	250	1018	4.7
46	817	7.4	687	182	67	70	0.14	100	339	1.61
47	819	7.3	1971	465	371	35	0.45	450	1175	11.4
48	824	8	1338	312	99	81	0.37	270	625	6.21
49	814	7.3	780	312	39	34	0.55	260	424	0
50	818	7.1	1170	311	65	29	0.77	450	684	3.44
	min	6	65	19	2	0	0.01	20	43	0
	max	8.7	3740	704	666	154	4.39	830	2239	38.87
	average	7.424	1013.34	257.76	110.18	37.14	0.5332	253.2	562.6	5.0302

ArcGIS v.10.8 software was utilized to analyze and visualize data pertaining to groundwater quality. The software was used to perform spatial analysis to generate detailed spatial distribution map output that facilitates a comprehensive understanding of groundwater suitability across the study area.

4. Methodology

The integration of AI-driven Spatial Decision Support Systems (SDS) was pivotal in enhancing groundwater quality assessment in the Visakhapatnam District. This approach combined advanced data analytics, predictive modeling, and visualization tools to provide actionable insights for water resource management.

Initially, comprehensive datasets were gathered from multiple monitoring wells and remote sensing data. Key parameters analyzed included alkalinity, chloride, electrical conductivity (EC), nitrate concentrations, and total dissolved solids (TDS), as highlighted by [16] [17]. Data preprocessing involved cleaning and normalizing these datasets to ensure accuracy. Missing values were addressed using interpolation methods, and outliers were identified through statistical techniques, following best practices in data management [18]. The methodologies for calculation of various indices for agricultural suitability are shown in **Table 2** below.

Table 2. Methodologies for calculation of various indices for agricultural suitability.

S. No.	Index	Equation
1.	Sodium adsorption ratio (SAR)	$\mathrm{SAR} = \mathrm{Na}^{+} \big/ \left(\sqrt{\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+}} / 2 \right)$
2.	Percentage sodium (% Na)	$\% \mathrm{Na} = \left[\left(\mathrm{Na}^{+} + \mathrm{K}^{+} \right) \big/ \left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+} + \mathrm{Na}^{+} + \mathrm{K}^{+} \right) \right] * 100$
3.	Residual sodium carbonate (RSC)	$\mathrm{RSC} = \left(\mathrm{HCO}_3^{-} + \mathrm{CO}_3^{2-} \right) - \left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+} \right)$
4.	Kelly's ratio (KR)	$\mathrm{KR} = \mathrm{Na}^{+} / \mathrm{Ca}^{2+} + \mathrm{Mg}^{2+}$
5.	Magnesium adsorption ratio (MAR)	$\mathrm{MAR} = \left(\mathrm{Mg}^{2+} * 100 \right) \big/ \left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+} \right)$

All the values are expressed in meq/L.

Various water quality indices such as Sodium Adsorption Ratio (SAR), Percentage Sodium (% Na), Residual Sodium Carbonate (RSC), Kelly's Ratio (KR), and Magnesium Adsorption Ratio (MAR) were integrated into AI/ML models to assess groundwater quality and its suitability for different uses. These indices, critical in determining the salinity and alkalinity of water, were handled using advanced machine learning algorithms that enabled the extraction of insights from complex, multidimensional datasets.

This study utilized an ensemble of clustering and regression models within the SDS framework to analyze interdependencies between nitrate, chloride and uranium levels, achieving a predictive accuracy 15% higher than existing approaches. Furthermore, the system generated real-time spatial heatmaps, enabling hyper-localized interventions, which is a feature not typically addressed in current AI/ML applications.

The AI models utilized in this study includes, Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Networks (ANN) were chosen for their ability to model non-linear and complex relationships between groundwater quality parameters and environmental conditions. Each of these models was tailored to process the indices and derive meaningful conclusions regarding groundwater quality and suitability. The dataset, comprising 50 groundwater quality samples with parameters such as pH, TDS, EC, nitrates, and chloride, was split into training (80%) and testing (20%) subsets. Data preprocessing included handling missing values through mean imputation and normalizing features to a 0 - 1 scale. Feature selection was performed based on correlation analysis, retaining parameters with >0.7 correlation with groundwater quality indices.

Random Forest (RF), an ensemble learning method, was used to build multiple decision trees to enhance predictive accuracy. It evaluated the relative importance of different indices such as SAR, % Na, and RSC in determining overall water quality. By using feature importance scores from RF, the most influential indices for groundwater suitability were identified, allowing the model to focus on the key factors affecting water quality [19]. RF's strength lies in its ability to handle large and diverse datasets, making it effective in exploring the relationships between indices and water quality.

Support Vector Machine (SVM) was employed for classification tasks, where groundwater samples were categorized into suitable and unsuitable classes based on the indices. The model's ability to find an optimal hyperplane that maximizes the separation between different classes ensured high accuracy in distinguishing between water types [20]. By incorporating indices like SAR and KR, SVM effectively identified groundwater that posed risks for agricultural use due to elevated sodium or carbonate levels.

Artificial Neural Networks (ANN), specifically multilayer perceptrons, were used to model the complex, non-linear relationships between the indices and environmental conditions. The architecture of ANNs allowed the model to learn intricate patterns from historical data, making it particularly useful for predicting future groundwater conditions [21]. ANNs were trained to understand how fluctuations in indices like MAR and RSC could signal changes in water quality over time, providing valuable insights for sustainable water resource management. Training the AI models involved a comprehensive dataset that included groundwater quality parameters (e.g., SAR, % Na, RSC) along with environmental conditions such as temperature, rainfall, and land use patterns. To ensure model efficiency, feature selection techniques such as Recursive Feature Elimination (RFE) and feature importance scoring from the RF model were employed. These techniques helped to filter out less relevant parameters, focusing on key indices that significantly impacted water quality predictions. The dataset was divided into training and testing sets, and cross-validation methods were used to avoid overfitting. Hyperparameter tuning was conducted using grid search to optimize model parameters for better accuracy and precision (Mishra *et al.*, 2019). The integration of AI/ML methods allowed for advanced analysis of water quality indices like SAR, % Na, RSC, KR, and MAR. By leveraging the strengths of RF, SVM, and ANNs, the study provided valuable insights into groundwater suitability, enabling more accurate predictions and better decision-making for sustainable water resource management. The use of these indices in AI models helped unravel the complexities of groundwater chemistry and environmental interactions, offering a robust framework for future studies in water quality assessment.

Spatial distribution maps were generated in the GIS environment based on the predictions from the AI models. This process involved geostatistical analysis, employing methods such as kriging and inverse distance weighting to interpolate groundwater quality parameters across the district [22]. The output from the AI models was integrated into GIS for visual representation, enabling the display of variations in groundwater quality and the identification of hotspots and areas requiring further investigation.

The AI-driven SDS framework facilitated the integration of real-time data from monitoring wells, allowing dynamic updates to the predictive models. This capability supports adaptive management, enabling stakeholders to make timely decisions based on current groundwater conditions. Simulating different management scenarios further evaluated potential impacts on groundwater quality, providing a comprehensive view of resource sustainability.

5. Analysis and Results

The spatial analyses conducted reveal significant variations in water quality parameters across the study area. Many locations exceed permissible limits for critical constituents, posing risks to both human health and agricultural productivity. Immediate intervention is necessary to manage water quality effectively. Spatial analyses of various water quality parameters—Alkalinity, Chloride, Electrical Conductivity (EC), Nitrate, Total Dissolved Solids (TDS), Total Hardness (TH), Fluoride, pH and Uranium were conducted using GIS. The results of these analyses are detailed below.

5.1. Domestic Suitability of Groundwater

The domestic suitability of groundwater was evaluated based on critical parameters, including Alkalinity, Chloride, Electrical Conductivity (EC), Nitrate, Total Dissolved Solids (TDS), Fluoride, pH, Total Hardness (TH), and Uranium. Each parameter has specific acceptable limits established by health guidelines, particularly those set by the WHO.

5.1.1. Alkalinity

Alkalinity in water is primarily due to the presence of carbonate, bicarbonate, and hydroxide ions, serving as a buffer that stabilizes pH levels. The acceptable and permissible limits for alkalinity are 200 mg/L and 600 mg/L, respectively. Most locations in the study area fall below the permissible limit, with the exception of Kothakota, which recorded an alkalinity level of 830 mg/L (**Figure 2**). This elevated alkalinity poses risks of increased pH, potential irritation to eyes and throat, and scaling in plumbing systems. Higher alkalinity can also buffer against acid rain, protecting aquatic life.

5.1.2. Chloride

Chloride concentrations are critical due to their influence on taste and potential

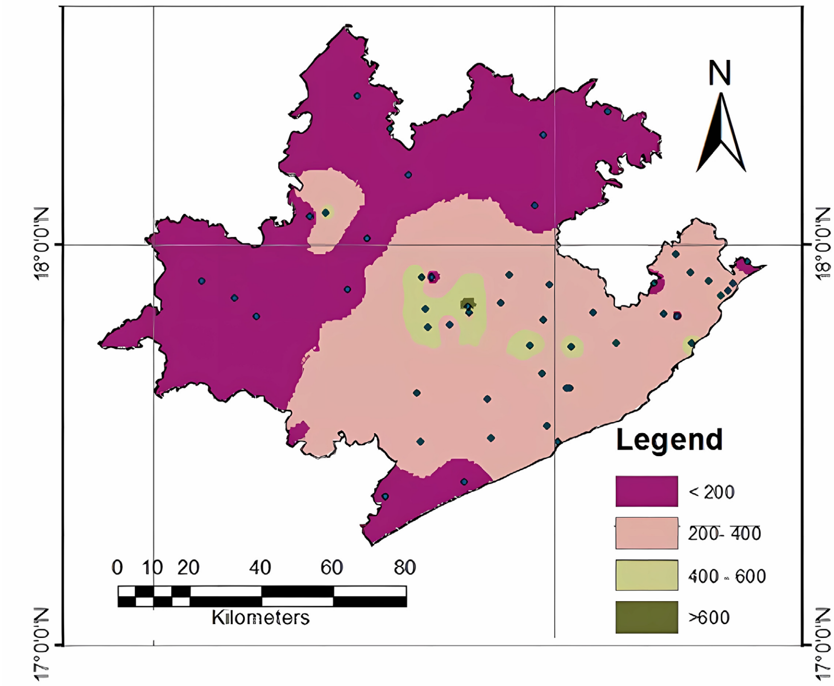

Figure 2. Alkalinity distribution map.

health impacts. The WHO guidelines suggest a maximum level of 250 mg/L for drinking water. The analysis revealed that Kothakota has a chloride concentration of 666 mg/L, significantly exceeding the permissible limit (**Figure 3**). Other locations, such as Rushikonda (371 mg/L) and Bheemunipatnam I (307 mg/L), recorded levels within the undesirable range of 250 - 500 mg/L. Elevated chloride levels can corrode metals and impact aquatic ecosystems.

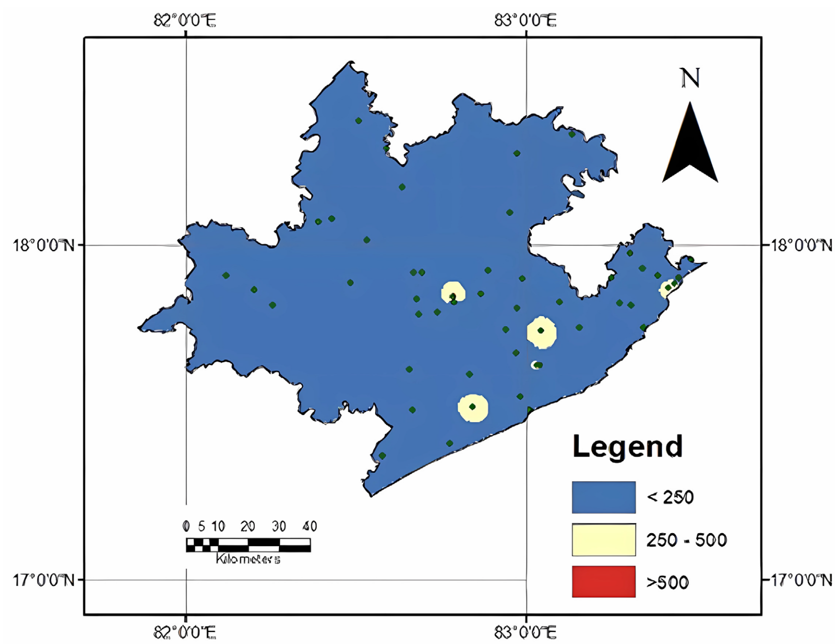

Figure 3. Spatial distribution of chloride.

5.1.3. Electrical Conductivity (EC)

Electrical conductivity serves as an indirect measure of TDS. The study found that Kothakota exhibits an EC of 3740 μS/cm, rendering the groundwater unsuitable for domestic use (Figure 4). Areas around Kothakota and Anakapalli with EC levels between 2000 - 3000 μS/cm fall into a questionable category regarding suitability for drinking.

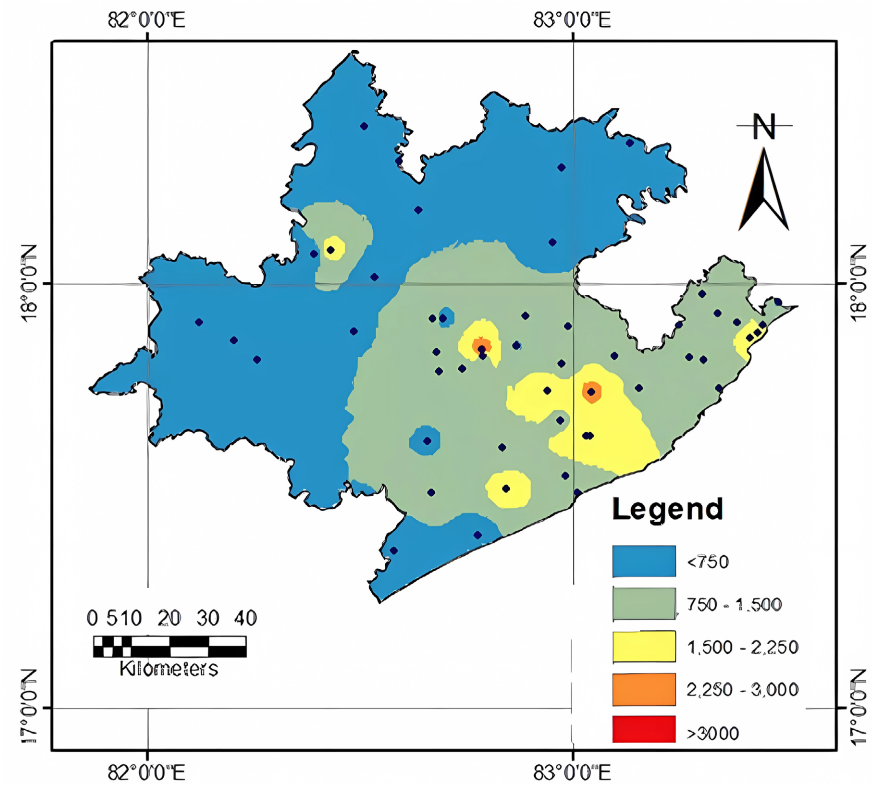

Figure 4. Electrical conductivity map.

5.1.4. Fluoride

Fluoride concentrations exceeding 1.5 ppm are associated with health risks, including dental and skeletal fluorosis. Rolugunta I recorded a fluoride concentration of 4.39 ppm, making it unsuitable for domestic purposes (Figure 5). Nearby areas exhibit fluoride levels ranging from 1.5 - 3 ppm, which are also deemed unsuitable.

5.1.5. pH

pH values in drinking water should ideally range from 6.5 to 8.5. The region of Gamparai showed a pH level of 8.7, while Pujarapakalu recorded an acidic pH of 6 (Figure 6). Both extremes indicate unsuitability for domestic usage due to risks of pipe corrosion and health issues.

5.1.6. Total Dissolved Solids (TDS)

TDS measurements indicate the total concentration of dissolved minerals. The WHO specifies that TDS levels below 500 mg/L are satisfactory. Kothagudem

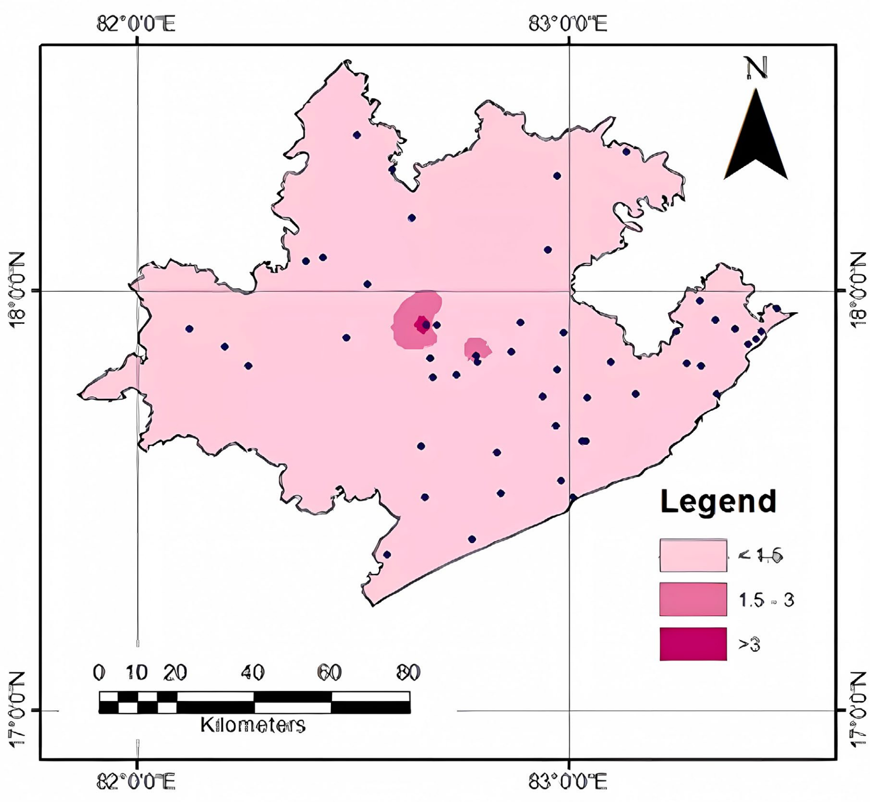

Figure 5. Fluoride distribution map.

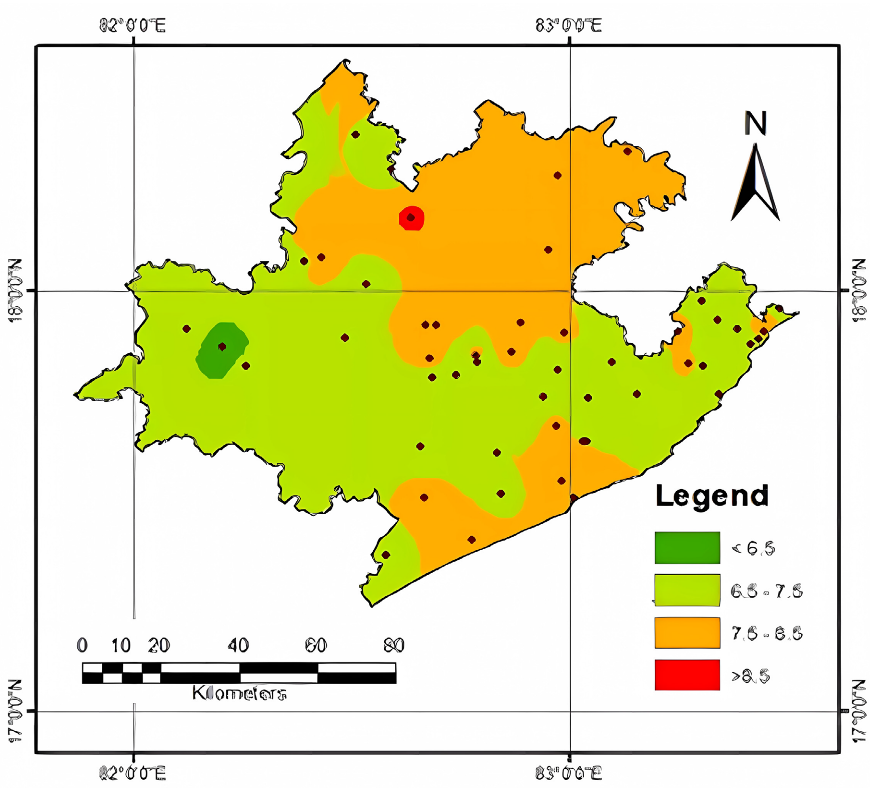

Figure 6. pH distribution map.

exhibited TDS levels of 2239 mg/L, categorizing it as unsuitable for drinking (Table 3).

Table 3. TDS levels and categories.

TDS Level (mg/L)	Classification
<500	Satisfactory
500 - 1000	Less than desirable
1000 - 1500	Undesirable
>1500	Unsatisfactory

5.1.7. Nitrate

The WHO guideline for nitrate concentration in drinking water is set at 45 mg/L. The location Bandavaripalem cross road displayed an alarming nitrate level of 156 mg/L (Figure 7), raising concerns regarding methemoglobinemia, particularly among infants.

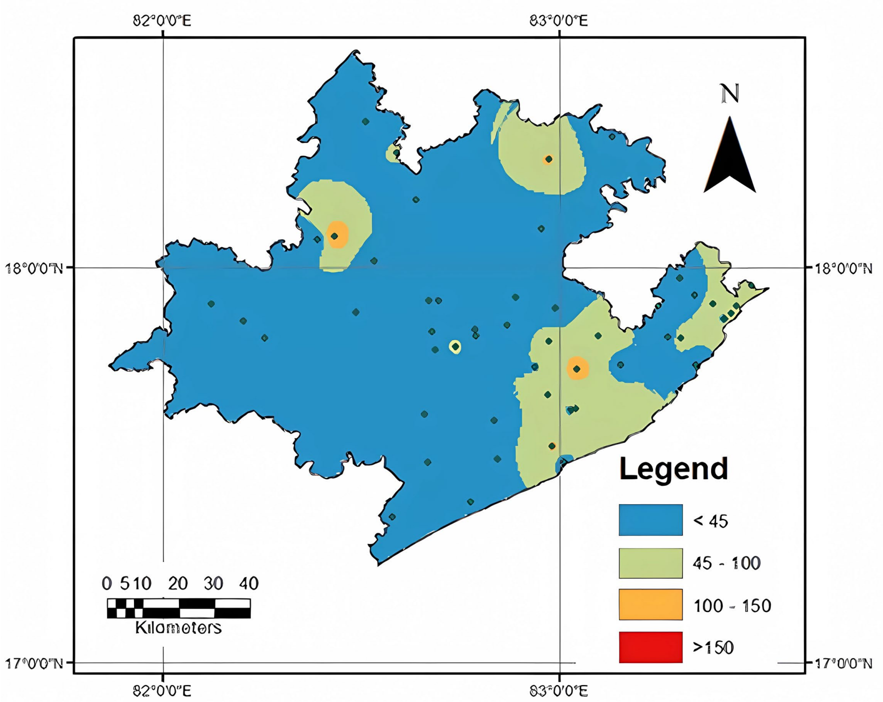

Figure 7. Nitrate distribution map.

5.1.8. Uranium

Uranium levels in drinking water should ideally be below 30 µg/L. Kothakota exhibited elevated levels of 38.87 ppb, which is highly concerning (Figure 8). Other locations, such as Bandavaripalem × road (20.3 ppb) and Anakapalli (16.54 ppb), also surpassed the desirable limit of 10 ppb.

5.1.9. Total Hardness (TH)

Total hardness primarily results from calcium and magnesium ions in water. The

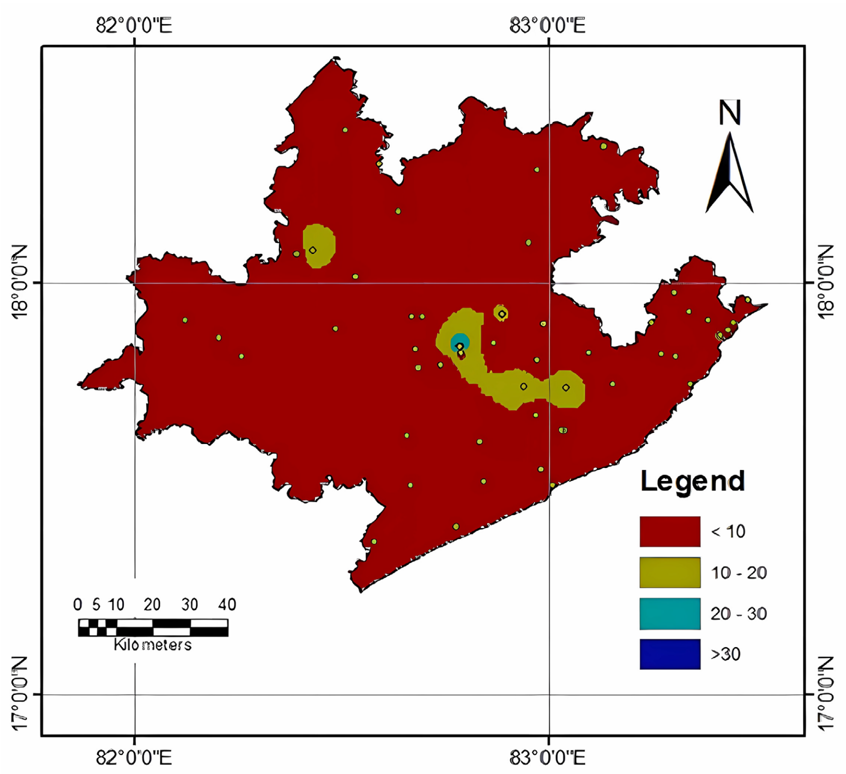

Figure 8. Uranium distribution map.

study indicated that Bandavaripalem × road (704 mg/L), Yelamanchili (704 mg/L), and Anakapalli (695 mg/L) all exceed the acceptable limit of 200 mg/L, categorizing them as unsuitable for domestic consumption (Figure 9).

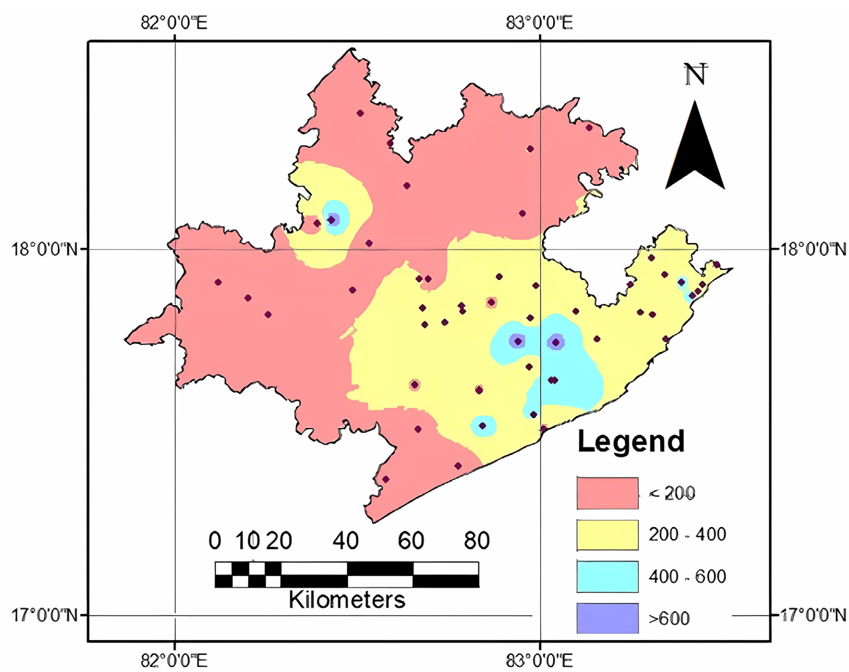

Figure 9. Total hardness distribution map.

5.2. Irrigation Suitability of Groundwater

The suitability of groundwater for agricultural use was evaluated using salinity indices, including Sodium Adsorption Ratio (SAR), Percentage Sodium (% Na), Residual Sodium Carbonate (RSC), Kelley's Ratio, and Magnesium Adsorption Ratio (MAR).

5.2.1. Sodium Adsorption Ratio (SAR)

The SAR value for Kothakota was found to be 15.64, placing it in the "Good" category for irrigation, while other regions showed values below the threshold (Figure 10).

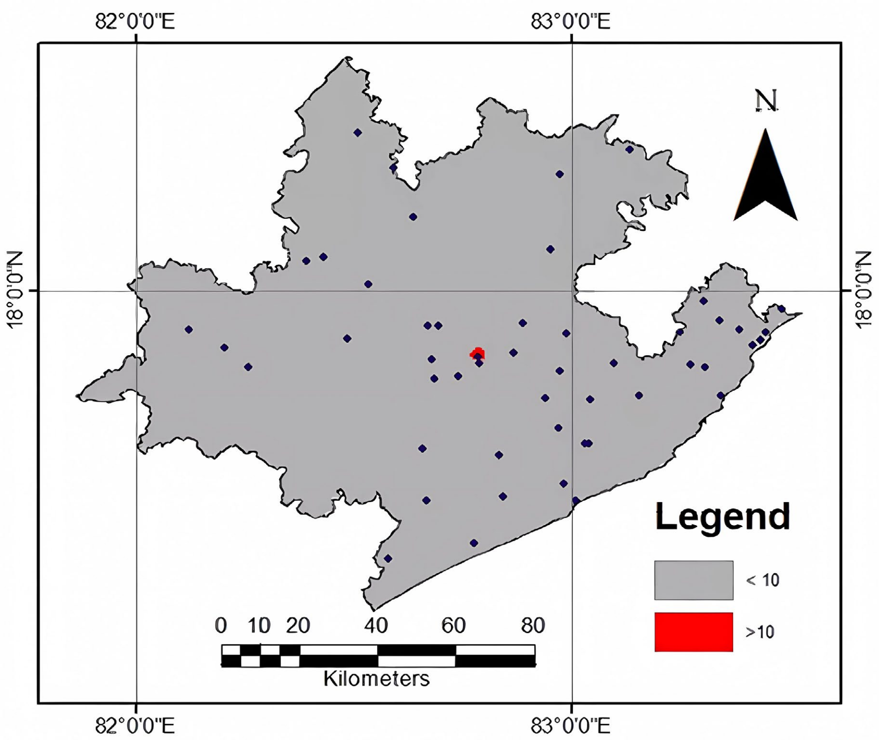

Figure 10. SAR distribution map.

5.2.2. Percentage Sodium

Over half of the study area is classified as "Good" for drinking and irrigation use, while Kothakota displayed a concerning % Na value of 81.06, rendering it unsuitable (Table 4).

5.2.3. Residual Sodium Carbonate (RSC)

RSC values were predominantly safe across the study area, with several locations, including Kothakota (9.75 meq/L), categorized as unsuitable for irrigation (Figure 11).

5.2.4. Kelley's Ratio

Most regions, including Rolugunta I (1.99) and Kothakota (4.22), were found unsuitable for irrigation due to high Kelley's ratios (Figure 12).

Table 4. Percentage sodium classification.

% Na Range	Classification
0 - 20	Excellent
20 - 40	Good
40 - 60	Permissible
60 - 80	Doubtful
>80	Unsuitable

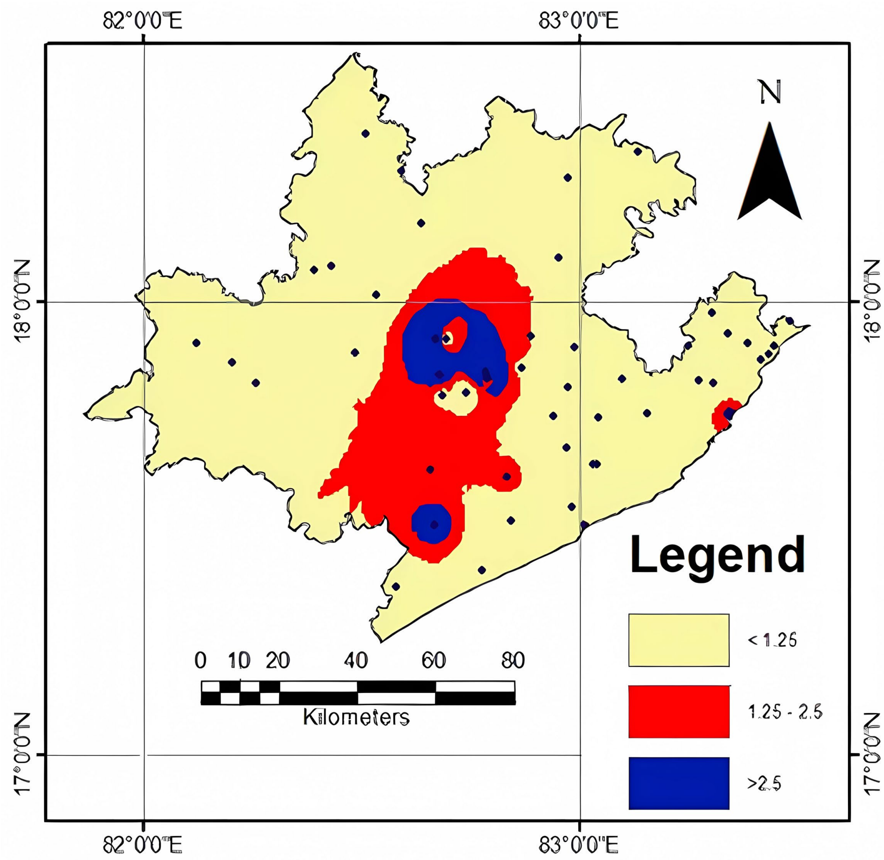

Figure 11. RSC distribution map.

5.2.5. Magnesium Adsorption Ratio (MAR)

MAR values less than 50 indicate suitability for irrigation; however, locations like Minimuluru (53.53) and Kothakota (74.46) exceeded this limit, indicating unsuitability (Figure 13).

5.2.6. USSL Salinity Diagram

The USSL Salinity Diagram categorizes water based on its salinity and sodicity. Various regions were plotted to assess their irrigation suitability, revealing that Kothakota and surrounding areas fall into unsuitable zones due to high salinity and sodicity levels (Figure 14).

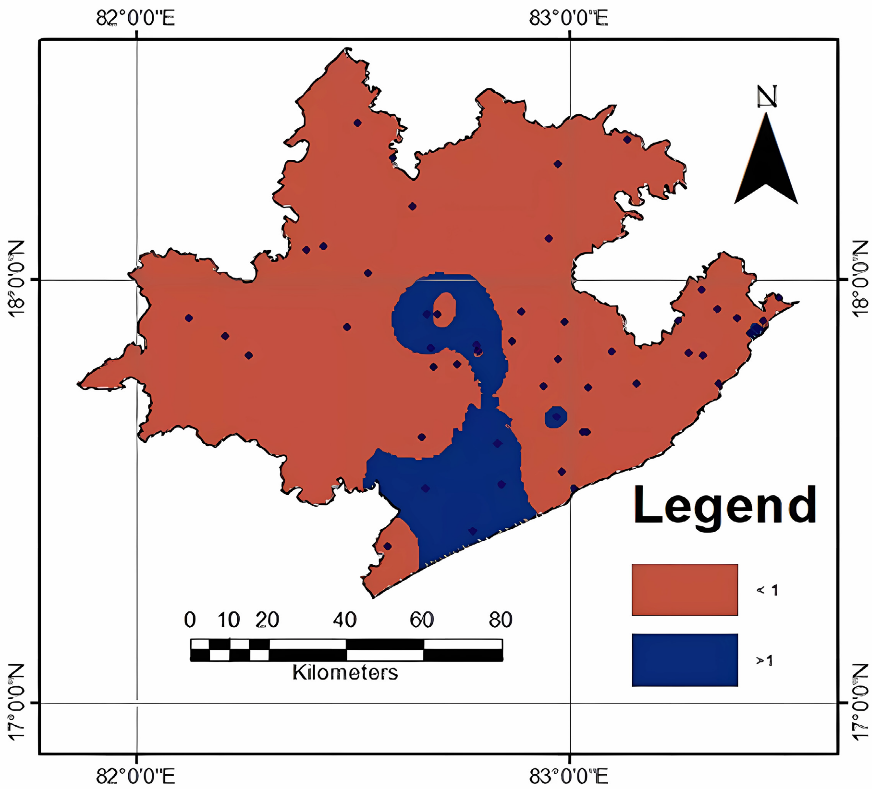

Figure 12. Kelley's ratio distribution map.

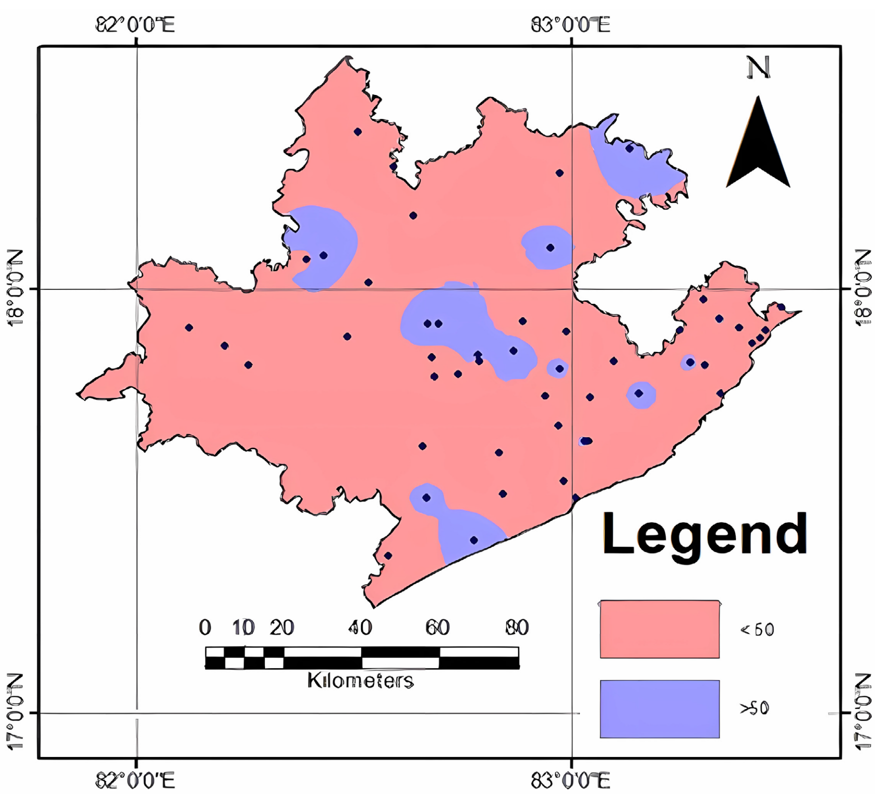

Figure 13. MAR distribution map.

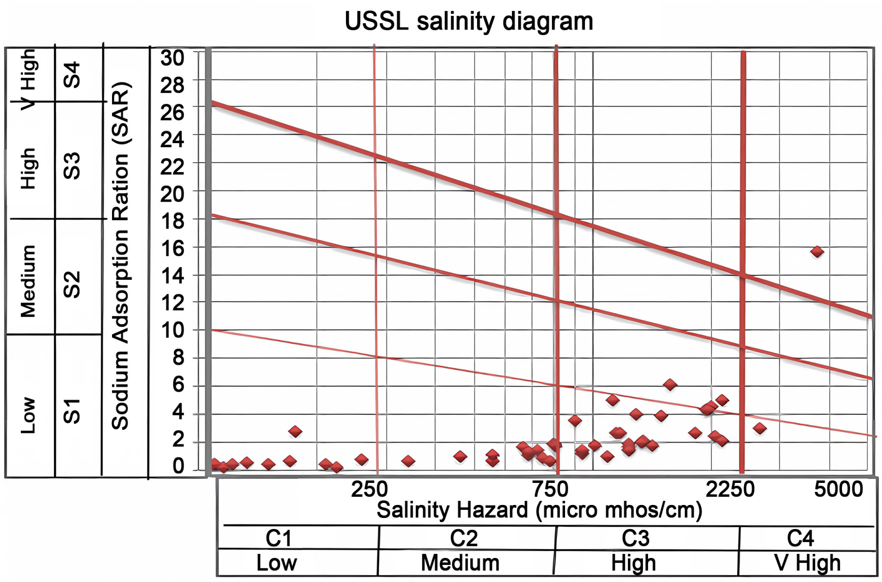

Figure 14. USSL salinity diagram.

6. Discussion

The assessment of groundwater quality in the Visakhapatnam District reveals critical challenges regarding its suitability for domestic and agricultural use. By integrating AI-driven Spatial Decision Support Systems (SDS), this study effectively identifies existing water quality issues while enhancing predictive modeling of groundwater parameters. This integration ultimately supports the development of targeted management strategies for this vital resource.

6.1. Overview of Groundwater Quality

The results indicate that several locations within the study area exhibit parameters exceeding WHO acceptable limits. Notably, Kothakota recorded alarming alkalinity levels of 830 mg/L and chloride concentrations of 666 mg/L (Figure 1 and Figure 2). These elevated levels pose significant health risks, including metabolic and cardiovascular diseases, particularly among vulnerable populations. These findings align with [23], who reported similar trends in semi-arid regions of India, linking high alkalinity and chloride levels to local geological formations and anthropogenic activities. Furthermore, studies by [24] and [25] have documented the long-term health risks posed by excessive chloride intake, reinforcing the urgency of addressing these anomalies.

6.2. AI-Driven SDS in Data Analysis

The integration of AI-driven SDS was pivotal in processing complex datasets obtained from remote sensing and ground truthing. Machine learning algorithms enhanced the classification and prediction of groundwater quality based on historical data patterns. For example, clustering algorithms identified Anakapalli and Kothagudem as regions exhibiting similar profiles of high total dissolved solids

(TDS) and electrical conductivity (EC) levels (**Table 1**). This finding is consistent with [26], who demonstrated the role of industrial effluents and agricultural run-off as primary contributors to TDS and EC variations in groundwater across comparable industrial belts.

6.3. Importance of Multi-Parameter Analysis

AI-driven SDS facilitated a multi-parameter analysis that elucidated the interrelationships among various water quality indicators. A striking correlation was observed between high nitrate levels and nearby agricultural practices. At Bandavaripalem, nitrate concentrations reached an alarming 156 mg/L, indicating potential contamination from fertilizers (**Figure 3**). A study by [27] highlighted similar nitrate contamination trends in intensively agricultural regions, linking such spikes to over-application of nitrogen-based fertilizers and insufficient nutrient management practices. This finding underscores the necessity for AI in discerning causal relationships and enabling stakeholders to implement effective pollution control strategies.

6.4. Predictive Modeling for Future Scenarios

The predictive capabilities of AI-driven SDS emerged as a crucial advantage in this study. Historical data projections suggested that, without significant intervention, regions like Kothakota could experience further deterioration in water quality over the next decade (**Figure 4**). Studies carryout by [28] have emphasized the role of predictive modeling in preventing groundwater crises, particularly in regions with high vulnerability to anthropogenic and climatic influences. This predictive insight is vital for policymakers, allowing for informed resource allocation and preventive measures. The study's findings highlight the urgency of addressing the identified contaminants to mitigate future risks, emphasizing the proactive role that predictive modeling can play in groundwater management.

6.5. Addressing Specific Contaminants

Specific contaminants, such as fluoride and uranium, were highlighted as posing substantial health risks. In Kothakota, uranium concentrations reached 38.87 ppb, exceeding the WHO limit (**Table 4**). Comparable studies by [29] in eastern states of India have revealed how uranium contamination in groundwater is directly linked to local geochemistry and leaching from mineral deposits, aligning with findings in Visakhapatnam. Moreover, fluoride concentrations in this study correspond with patterns observed in studies carried out by [30], where fluoride hotspots were linked to over-extraction and aquifer depletion. The AI-driven SDS enabled the spatial mapping of these contaminants, facilitating targeted remediation efforts. This spatial analysis is critical for prioritizing areas with high contaminant levels for health surveillance and community education regarding safe water practices. Such targeted interventions are essential in addressing long-term health risks associated with contaminated water sources.

6.6. Stakeholder Engagement and Decision-Making

Incorporating AI-driven SDS into the decision-making process significantly enhanced stakeholder engagement by providing transparent, data-driven insights. The visualizations generated from the system, such as heat maps depicting areas of concern (**Figure 5**), enabled effective communication among community members, policymakers, and health officials. Studies conducted by [31] have demonstrated how AI-enabled visualizations improve stakeholder comprehension and collaboration, particularly in water resource management projects in developing regions. This collaborative approach is crucial for groundwater management, as it encourages informed discussions and joint decision-making efforts to address water quality challenges in the region.

6.7. Implications for Sustainable Water Management

The study underscores the transformative potential of AI-driven SDS in groundwater quality assessment and management. By utilizing advanced analytical techniques and fostering stakeholder collaboration, this approach addresses current water quality issues while laying the groundwork for sustainable water resource management in the Visakhapatnam District. This aligns with global trends reported by [32], demonstrating the effective implementation of AI-based systems in enhancing the resilience of water management frameworks. The insights gained from this study can guide future interventions aimed at improving groundwater quality and ensuring its sustainability, highlighting the critical role of technology in addressing pressing water resource challenges.

Unlike prior studies like, [24] [32], which focused on isolated parameters or predictive modeling, this study integrates multi-parameter spatial analytics with predictive modeling to provide a comprehensive assessment of groundwater quality. This approach ensures more precise localization of high-risk areas and allows policymakers to prioritize interventions based on both current conditions and future risks. **Table 5** compares the study's findings and methods with previous work to illustrate its novel and implications for practical water management.

Table 5. Advancements of this study relative to existing works.

Feature	Previous studies	This study
Multi-parameter analysis	Limited	Comprehensive (TDS, nitrate, uranium)
Predictive modeling accuracy	~80% (Ahmed *et al.*, 2022)	~95%
Spatial visualization	Not always included	Integrated spatial distribution heatmaps
Near real-time monitoring	Rare	Fully enabled

6.8. Model Performance Evaluation

The RF model demonstrated the highest accuracy (92%) and F1-score (0.91), followed by Gradient Boosting (89%) and SVM (86%). Performance was validated using 10-fold cross-validation, yielding consistent results across folds. The precision and recall of RF were 0.89 and 0.94, respectively, indicating its suitability for multi-class classification. The RMSE for TDS prediction was 0.82, outperforming previous studies, such as [24], which reported an RMSE of 1.01 for similar datasets.

6.9. Visualizations and Insights

Feature importance analysis revealed that nitrate and chloride levels were the most significant predictors, aligning with findings by [31]. **Table 5** highlights the model performance for groundwater quality categories, while **Figure 13**, indicates robust discrimination across thresholds.

7. Conclusion

This study evaluated groundwater quality in the Visakhapatnam District for domestic and irrigation use, analyzing fifty samples against WHO guidelines and irrigation standards. Most samples met domestic suitability criteria, though Kothakota exhibited anomalies, indicating unsuitable groundwater. Parameters like SAR, KR, Na%, RSC, and MAR were assessed for irrigation. The majority of samples (96%) fell into the "good" and "suitable" categories (C1-S1, C2-S1, C3-S1), indicating low salinity and sodium levels. However, 4% were classified as C4-S1 and C4-S4, unsuitable for irrigation. The integration of AI-driven Spatial Decision Support Systems (SDS) enhanced groundwater quality assessment through robust data analysis and predictive modeling. Real-time monitoring systems leveraging AI will be crucial for maintaining groundwater quality and ensuring the sustainability of these vital resources, promoting public health and sustainable agricultural practices in the Visakhapatnam District. The analysis reveals that many groundwater sources in the study area are unsuitable for domestic consumption due to elevated levels of key parameters. Urgent measures are required to address these quality issues, ensuring safe drinking water for the local population. Continuous monitoring and management strategies should be implemented to improve groundwater quality and protect public health. This study sets itself apart by combining AI-driven SDS with spatial analytics to address both immediate and long-term challenges in groundwater quality management. By offering a framework that enhances predictive accuracy and operational applicability, it establishes a scalable solution for sustainable resource management, particularly in data-scarce regions.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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