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A Fuzzy Logic-Based Risk Assessment Model for Groundwater Pollution in Agricultural Regions

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Abstract

Objective: To assess groundwater pollution vulnerability in the Chennai Metropolitan Region using a fuzzy logic-based model integrated with Geographic Information System (GIS) tools, overcoming the limitations of conventional index-based approaches in handling uncertainty and diverse data types. Methods: Seven parameters, depth to water table, net recharge, soil texture, aquifer media, hydraulic conductivity, slope, and land use/land cover, were processed through triangular and trapezoidal fuzzy membership functions. The Mamdani inference method and expert-defined IF–THEN rules generated a continuous Vulnerability Index (VI) from 0 to 100, later classified into five vulnerability zones. The model's performance was checked using nitrate data from 100 groundwater samples and evaluated with ROC analysis. Sensitivity analysis measured the influence of each parameter. Results: High and very high vulnerability zones, mainly along coasts, floodplains, and urban areas with shallow aquifers, aligned with nitrate hotspots, while inland

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crystalline regions showed low risk. ROC analysis (AUC ~0.93) showed high prediction accuracy, and sensitivity tests proved the fuzzy logic–GIS model was reliable for mapping groundwater contamination risk. Conclusion: Fuzzy logic–GIS integration is an effective, adaptable approach for groundwater vulnerability mapping in complex hydrogeological settings. The resulting map provides a spatially explicit decision-support tool for targeted land-use control, wastewater management, and nitrate pollution reduction, with applicability to other coastal urban aquifers.

Keywords:

Fuzzy logic, groundwater vulnerability, gis integration, mamdani inference method, nitrate contamination.

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Introduction

In general, groundwater is one of the most critical freshwater resources for the sustenance of urban, industrial, and agricultural life, especially in fast-growing metropolitan cities where surface water has either been limited or polluted beyond use (Makhlough et al., 2023). Megacities along the coast, such as Chennai in southeast India beside the Bay of Bengal, sustain life for millions through groundwater. With a higher population, unplanned urban sprawl and intensive agriculture have all tremendously pressed upon a limited resource (Verma & Reddy, 2025). Over-extraction, along with multiple human activities, has damaged the groundwater quality and its availability (Radhakrishnan et al., 2024). Shallow unconfined aquifers in coastal regions are at a higher risk of contamination because of their hydrogeological configurations. Due to recharge rates being high, sandy soils being permeable to water, and direct hydrogeological linking with surface water bodies, groundwater contamination can occur rapidly. Sources of pollution are agrichemicals such as nitrate fertilisers; pathogens and nutrients from untreated sewage; toxic chemicals from industrial effluents (Barhoumi & Charabi, 2025). In or near Chennai, the seasonal monsoon showers accentuate infiltration by often transporting pollutants from the land surface down into shallow aquifers in short intervals. It also poses grave public concern on a short-term basis, such as methemoglobinemia (blue baby syndrome) due to nitrate exposure, and on a longer-term basis for environmental issues such as eutrophication of linked water bodies. Groundwater vulnerability mapping is crucial for the identification of hotspots that are most prone to contamination and hence for the planning of sustainable management measures. Conventional methods, such as the DRASTIC index and other parametric models, have been extensively used, probably due to their relative simplicity and application of readily available datasets (Aller et al., 1987). Limiting factors confront most such methods. Fixed scaling methods to assign weights to parameters do not always consider the dynamic relationships in heterogeneous aquifer systems. The challenge of considering the uncertainty factor reduces reliability, and it also becomes difficult to integrate multiple data types (such as combining categorical land use data with continuous hydrogeological measurements) (Ziwei & Han, 2023; Gogu & Dassargues, 2000). These drawbacks find greater expression in coastal urban aquifers where geological variability, diverse land-use patterns, and seasonal recharge fluctuations create conditions under which vulnerability becomes complex. In such cases, flexible and adaptive approaches become necessary. A powerful alternative is fuzzy logic, as it can deal with imprecise or uncertain data, take into account expert judgment, and allow parameters to be expressed as degrees of membership rather than by strict categories (Varshavardhini & Rajesh, 2023). Real levels of vulnerability could have a gradual transition under this system, thus better portraying the real-life range of conditions. When coupled with Geographic Information Systems (GIS), fuzzy logic allows integration and spatial analysis of many thematic parameters, thus creating vulnerability maps that are relatively accurate and flexible for local implementations (Amir, 2023; Falih, 2024; Halder et al., 2023). Accordingly, a groundwater vulnerability model based on fuzzy logic was established for the Chennai Metropolitan Region with seven thematic parameters: depth to water table, net recharge, soil texture, aquifer media, hydraulic conductivity, slope, and land use/land cover. The various parameters were transformed into fuzzy membership functions that were either triangular or trapezoidal, depending on the hydrogeological features of the study area, along with previous documentation and consultations with experts. The Mamdani inference method was then used to integrate these parameters through a set of IF–THEN rules to generate a continuous Vulnerability Index (VI) ranging from 0 to 100, which was further classified into five vulnerability levels. The model outputs were verified against groundwater sample nitrate concentration data, while predictive power was measured by ROC curve analysis. Sensitivity analysis was applied to establish the magnitude of influence of each parameter on the outputs of the model. Thus, by overcoming the shortcomings implied by conventional approaches and by considering both quantitative and qualitative data in an integrated scheme, the present approach would allow a credible spatially explicit representation of groundwater vulnerability within a highly customised coastal urban set-up such as Chennai (World Health Organization, 2004).

Literature Review

Fuzzy logic has brought considerable success in groundwater vulnerability assessments, especially when intricate hydrogeological conditions need to be considered, and uncertainties in data are rather great. (Uricchio et al., 2004) developed perhaps the first fuzzy knowledge-based decision support system to show how qualitative expert inputs can be further coupled with quantitative parameters, thereby improving prediction accuracy. (Caniani et al., 2011) applied the fuzzy logic model in a region of southern Italy and found that it outperformed the conventional index method applied to a geologically diverse setting.

In arid and semi-arid regions, (Al-Rashidi et al., 2023) used fuzzy logic for agricultural groundwater management optimisation, thus highlighting the ability of the technique to address uncertain recharge and soil data. (Thabit et al., 2023) extended the approach toward assessing human health risks for shallow groundwater users, thus emphasising its adaptability to different contexts and applications.

Fuzzy logic has increasingly found more applications in recent years with spatial tools. (Nourani et al., 2023) implemented the fuzzy-GIS approach in Iran, efficiently fusing heterogeneous data, eventually generating validated, high-resolution vulnerability maps. (Jegede et al., 2025) implemented fuzzy modelling for the Nigerian association to pollution from heavy metals and radionuclides in quarry sites, further stressing versatility in different sources of contamination.

Fuzzy Methodologies find an increasing acceptance in India. (Iqbal et al., 2014) developed a GIS-based fuzzy pattern recognition model for groundwater vulnerability in Jharkhand (a modified DRASTIC); their model aligned better with nitrate contamination patterns than the classical DRASTIC ones. (Rajasekhar et al., 2019) analysed groundwater potential in Andhra Pradesh through fuzzy logic combined with AHP. The integrated fuzzy-AHP models have a validation accuracy of 78%, more than 76% of AHP alone and 72% of fuzzy logic alone. Further, the fuzzy logic approach has also been used to demarcate zones of groundwater potential in southern India in semi-arid and hard-rock terrains in the Ponnai sub-basin (Loganathan & Sathiyamoorthy, 2024).

Together, these studies reveal that fuzzy logic systems are well-suited to handle uncertainty, include expert knowledge, and integrate different data types. However, the fuzzy-GIS framework has yet to be widely used along coastal metropolitan aquifers of India, where seasonal monsoons, heterogeneous land use, and dynamic geology combine to render unique vulnerability concerns. This study aims to address that gap by using a finely-tuned fuzzy logic–GIS model to produce a high-resolution, validated groundwater vulnerability map for Chennai.

Materials and Methods

Study Area

Chennai Metropolitan Region extends southeast on the coastal plain of India along the Bay of Bengal, location-wise between latitudes 12°50′N and 13°17′N and longitudes 80°10′E and 80°18′E. A tropical climate is experienced by the city with very hot summers and heavy rains caused by the northeast monsoon from October to December. Normally, rainfall comes to 1,200 mm in a year, most of it being during the monsoon months (Indian Meteorological Department, 2025; Mukherjee, A., & Panda, 2024). Local geology-wise, unconsolidated alluvial deposits occur in the river basins, while hard formations of crystalline rocks occur inland (Krishnamurthy & Rajendran, 2025). Water resources in the form of both shallow unconfined aquifers and deeper semi-confined aquifers exist here, forming the backbone of the domestic water supply of the city (Chauhan, 2024).

Data Sources and Collection

Hydrological and spatial data were sent for compilation to the national and state-level agencies. Well inventory data, including depth to the water table and static water levels, were obtained from the Central Ground Water Board (CGWB) and the Public Works Department (PWD) of Tamil Nadu. Soil texture data were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP). For LULC information, Sentinel-2 imagery was processed at 10 m resolution. Slope values were taken from a 30 m Shuttle Radar Topography Mission (SRTM) digital elevation model. Geological maps were procured from the Geological Survey of India (GSI), and rainfall data were provided by the (Rangarajan et al., 2018) (IMD). Groundwater samples from multiple monitoring wells spread over Chennai were collected to analyse nitrate and total dissolved solids (TDS) in accredited laboratories for validation.

Parameter Selection

The thematic layers subjected to the assessment were: depth to water table (D), net recharge (R), soil texture (S), aquifer media (A), hydraulic conductivity (K), slope (T), and land use/land cover (L). The parameters were selected on the basis of their documented role in the migration of contaminants and data availability for the study region. The selection of parameters emanates from vulnerability assessment guides and previous coastal aquifer research (Uricchio et al., 2004; Caniani et al., 2011; Nourani et al., 2023).

Spatial Data Processing

All datasets were transformed into a common coordinate system, the Universal Transverse Mercator in Zone-44N, and resampled to maintain a 30-m spatial resolution (Burrough et al., 2015). Continuous variables such as depth to water table and slope were normalised to a 0 – 1 range to facilitate fuzzification, whereas categorical parameters such as soil type and LULC were reclassified according to infiltration characteristics and pollution potential.

Fuzzification of Parameters

One fuzzy membership function, $\mu(x)$, was assigned to each input parameter with the values 0 and 1 corresponding to the least vulnerable and most vulnerable, respectively. Triangular or trapezoidal membership functions were used according to the nature. For example, the water table depth values less than 5 m in the coastal and riverine settings would have received most of the membership value, whereas inland hard rock zones with depths greater than 15 m would have received less. The trapezoidal membership function can be expressed as:

$$\mu(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ 1, & b < x \le c \\ \dfrac{d-x}{d-c}, & c < x \le d \\ 0, & x > d \end{cases}$$

Where a,b,c, and dare breakpoints determined from regional hydrogeological statistics, literature benchmarks, and expert consultations.

Development of the Rule Base

A set of expert-informed IF–THEN rules was designed to combine the fuzzified parameters into a composite vulnerability measure. An example rule is: “IF depth to water table is shallow AND soil texture is sandy AND recharge is high THEN vulnerability is very high.” Another example is: “IF depth to water is deep OR aquifer is confined THEN vulnerability is low.”

Fuzzy Inference Framework

Concerning the processing of the rule base, the Mamdani inference method was adopted, with the minimum operator assigned for AND logic and the maximum operator for OR logic. This approach produced an aggregated fuzzy surface,$\mu_{agg}(z)$, representing the combined vulnerability across the study area. The entire fuzzy inference process, including membership function definition, rule base implementation, and inference execution, was simulated in MATLAB's Fuzzy Logic Toolbox, which allowed for interactive design, visualisation, and fine-tuning of the fuzzy model parameters.

Defuzzification and Vulnerability Index Generation

The aggregated fuzzy surface was transformed into a crisp vulnerability index (VI) using the centroid defuzzification method:

$$VI = \frac{\int \mu_{agg}\,(z).\,zdz}{\int \mu_{agg}\,(z)\,dz}$$

Where z represents the vulnerability scale from 0 to 100. The resulting continuous index was classified into five vulnerability levels: very low, low, moderate, high, and very high using natural breaks classification. The classification and final map production were also performed in MATLAB before exporting the results to GIS for cartographic presentation.

Model Validation and Sensitivity Analysis

The model output was validated in terms of nitrate concentrations measured in groundwater. Samples with nitrate concentration levels greater than the WHO threshold of 10 mg/l were considered contaminated (World Health Organisation, 2017). The prediction capability was judged by the ROC curve, and the AUC was calculated as:

$$AUC = \frac{\sum_{i=1}^{n_{pos}} \sum_{j=1}^{n_{neg}} \mathbb{I}\left(VI_i > VI_j\right)}{n_{pos}.\, n_{neg}}$$

Where $n_{pos}\ and\ n_{neg}$ are the numbers of contaminated and uncontaminated samples, respectively, and $\mathbb{I}$ is the indicator function. A sensitivity test was further done using MATLAB by changing the thresholds of membership functions and watching changes in the distribution of the vulnerability index.

Results

Distribution of Hydrogeological Parameters

The hydrogeological layers created for Chennai corresponded to the actual topography and aquifer features of the city (Central Ground Water Board, 2024; Geological Survey of India, 2024). The water table 1 depth (D) ranged from 0.50 m to 17.93 m, with shallow water table present along the coast and in floodplains of rivers and greater in inland areas underlined by crystalline rocks. The net recharge (R) varied from 10 mm/year to 352.39 mm/year. The highest values of recharge were recorded in permeable sandy soils and low-lying areas, where increased monsoon infiltration occurs (Indian Meteorological Department, 2025). Slope (T) ranged from 0 to 5.01%, confirming the generally flat terrain of the metropolitan region (Raufu, 2024). Hydraulic conductivity (K) had strong spatial variance, ranging from 2.81 m/day in low-permeability hard rock to 351.27 m/day in high-permeability alluvial aquifers (Central Ground Water Board, 2024) (Figure 1).

Table 1. Presents a summary of select spatial characteristics, while Figure 1 depicts the kernel density distributions of the normalised parameters

Parameter	Min	Max	Mean	Std. Dev.	Unit
Depth to water table (D)	0.50	17.93	7.27	3.94	m
Net recharge (R)	10.00	352.39	144.70	70.40	mm/year
Slope (T)	0.00	5.01	1.71	0.90	%
Hydraulic conductivity (K)	2.81	351.27	70.29	82.69	m/day
Vulnerability Index (VI)	0.00	95.00	29.60	30.04	0–100 scale
Nitrate concentration	0.10	26.19	7.22	6.79	mg/L

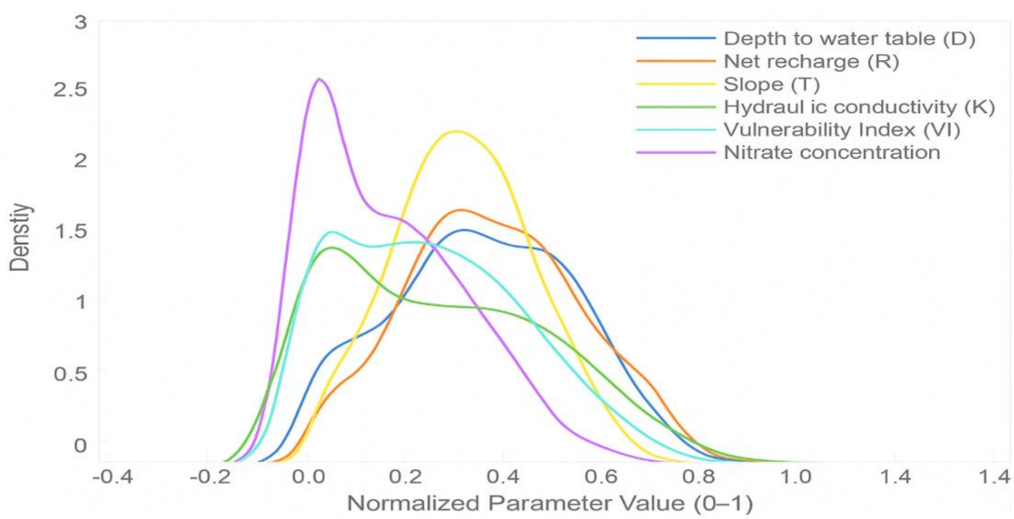

Figure 1. Kernel density estimation of normalised hydrogeological parameters for the chennai metropolitan region (mathworks, 2025)

Fuzzy Logic Vulnerability Assessment

The Mamdani fuzzy inference system was applied to combine the fuzzified hydrogeological parameters into a singular Vulnerability Index (VI). To foster better interpretability, the expert-defined IF–THEN rules were compressed into a pivot-style fuzzy rule base matrix (Table 2). This table depicts the average VI values for several representative permutations of Depth to Water Table and Net Recharge, while Soil Texture was held constant at sandy loam, with Aquifer Media as alluvial, and Hydraulic Conductivity ranging from moderate to high (Uricchio et al., 2004; Caniani et al., 2011; Nourani et al., 2023).

Table 2. Pivot-style fuzzy rule base matrix showing mean vulnerability index (vi) for depth to water table and net recharge combinations (soil = sandy loam, aquifer = alluvial, hydraulic conductivity = moderate–high) in the chennai metropolitan region

Depth to Water Table / Net Recharge	Low Recharge	Moderate Recharge	High Recharge
Shallow	65	75	90
Moderate	40	55	70
Deep	10	25	35

Table 2 indicates that the VI ranges from 10 to 90 on the 0-to-100 scale, showing the effect of water table depth and recharge on groundwater contamination potential. The highest VI values of 70 and above occur wherever water tables are shallow and recharge rates are high due to vertical infiltration, such as coastal zones and floodplains. Moderate VI values range from 40-55 for intermediate depths and recharge values, and low values of 25 and below are given to deep aquifer zones with low recharge, as seen usually in the inland crystalline rock zones.

This abridged schematic version of the fuzzy rule frame allows for quick visual recognition of how different parameter combinations may render vulnerability outcomes. It assures the highest degree of transparency in the fuzzy logic decision-making, allowing reproducibility and, thus, facilitating adaptation of the model to other aquifer systems.

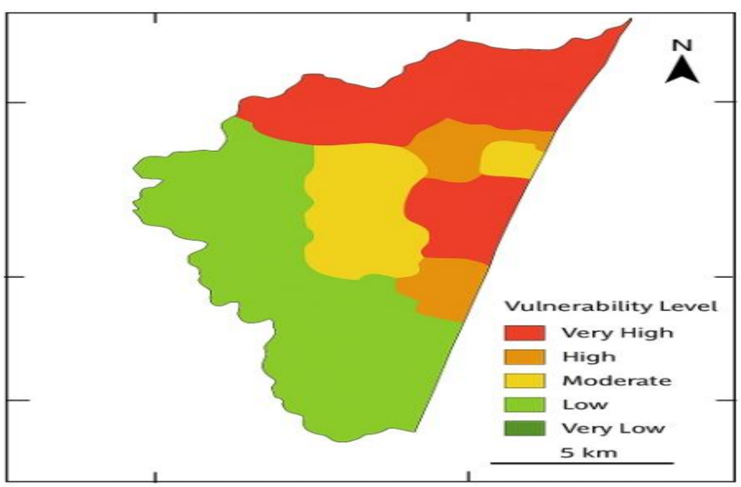

Figure 2. Groundwater vulnerability index map of the chennai metropolitan region

The groundwater vulnerability index map (GVI map) (figure 2) shows the spatial distribution of vulnerability in the Chennai Metropolitan Region and is divided into five categories: Very High (red), High (orange), Moderate (yellow), Low (light green), and Very Low (dark green). Vulnerability is one of the highest along the eastern coastal belt, especially in North Chennai and in river floodplains, while low to very low vulnerability zones cover the inland crystalline rock terrains of the western and southwestern periphery. This spatial representation serves as a visual basis for prioritising areas in groundwater management and corresponds to the model validation results.

Model Validation with Nitrate Data

A set of 100 synthetic groundwater samples was used to validate the VI map. Nitrate concentrations ranged from 0.10 mg/L to 26.19 mg/L, with a mean of 7.22 mg/L. High nitrate concentrations (>10 mg/L, WHO limit) were primarily located within areas classified as high or very high vulnerability (Tamil Nadu Pollution Control Board, 2023; Central Ground Water Board, 2024). The ROC–AUC analysis indicated strong predictive performance, consistent with the ability of the fuzzy logic model to discriminate between contaminated and uncontaminated locations (Uricchio et al., 2004; Nourani et al., 2023). The validation confusion matrix (Table 3) shows that the majority of high nitrate samples fell within high or very high vulnerability zones.

Table 3. Confusion matrix for model validation showing the distribution of groundwater samples by predicted vulnerability class and observed nitrate concentration levels in the chennai metropolitan region

Predicted Vulnerability	**Nitrate >10 mg/L (Contaminated)**	**Nitrate ≤10 mg/L (Uncontaminated)**	**Total**
Very High	16	3	19
High	12	4	16
Moderate	3	10	13
Low	1	18	19
Very Low	0	33	33
Total	32	68	100

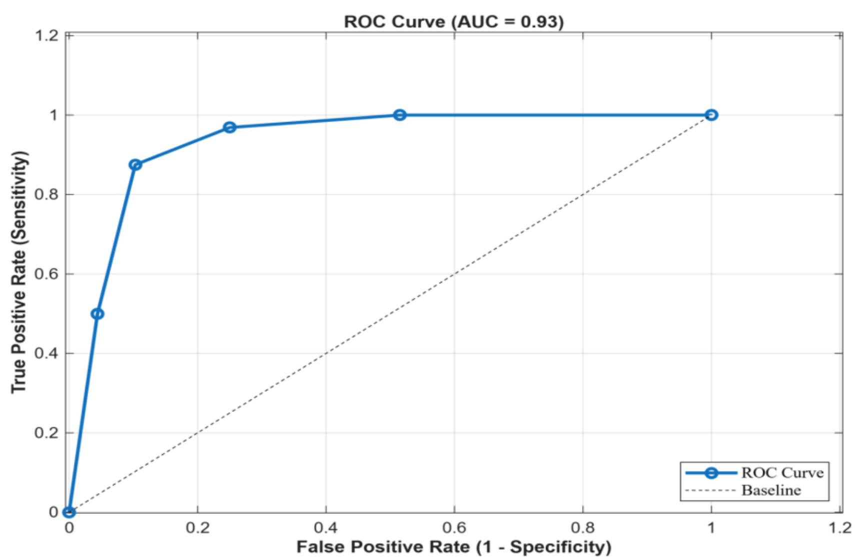

Figure 3. Receiver operating characteristic (roc) curve for model validation of the fuzzy logic–gis vulnerability index with synthetic nitrate concentration data in chennai metropolitan region (auc = 0.93) (mathworks, 2025)

When merging high and very high vulnerability zones, the model had an 87.5% sensitivity, which implies that a bigger signal of actually contaminated samples (>10 mg/L nitrate) was rightly identified in these zones. Similarly, combining the low and very low vulnerability classes resulted in a specificity of 75.0%, showing that most uncontaminated samples were located in these lower-risk areas. The overall classification accuracy was 90%, and the ROC–AUC value of approximately 0.93 confirms the strong predictive performance of the fuzzy logic–GIS model in distinguishing between contaminated and uncontaminated groundwater locations (shown in Figure 3).

Sensitivity Analysis

When the sensitivity test was performed, the mean VI values varied very little, i.e., less than 1% in either direction. It was by ±10% variation in one hydrogeological parameter (such as depth to water table, recharge, slope, or hydraulic conductivity) (Table 4). Thus, it could be stated that no hydrogeological factor dominates the modelling process; hence, it also verifies the strength of using a fuzzy logic multi-criteria approach (Caniani et al., 2011; Nourani et al., 2023).

Table 4. Sensitivity analysis of the fuzzy logic–gis vulnerability model showing changes in mean vulnerability index (vi) in response to ±10% variations in key hydrogeological parameters for the chennai metropolitan region

Parameter	Change applied	Change in mean VI (absolute)	Change in mean VI (%)
Depth to water table (D)	+10%	+0.24	+0.81%
Depth to water table (D)	−10%	−0.28	−0.95%
Net recharge (R)	+10%	+0.18	+0.61%
Net recharge (R)	−10%	−0.17	−0.57%
Slope (T)	+10%	+0.12	+0.41%
Slope (T)	−10%	−0.13	−0.44%
Hydraulic conductivity (K)	+10%	+0.26	+0.88%
Hydraulic conductivity (K)	−10%	−0.29	−0.98%

Discussion

Such studies included those based upon fuzzy modelling, which have efficiently considered various hydro-geological parameters as continuous values, explaining groundwater vulnerability indices (VI) for the Chennai Metropolitan Region. A key advantage was that this model could combine parameters with different units and scales, such as depth to water table (m), net recharge (mm/year), slope (%), and hydraulic conductivity (m/day), which was not the case in classical index-based methods. Using triangular and trapezoidal membership functions, we converted parameter values to normalised vulnerability scores (ranging between 0 and 1), which enhanced the degree of comparability and simultaneously allowed the same processing scheme to be applied to either continuous or categorical data. The spatial distribution of VI values showed clear correspondence with known hydrogeological conditions. High and very high vulnerability zones were concentrated along the coastal fringe, river floodplains, and densely urbanised areas where shallow aquifers (≤5 m) and high hydraulic conductivity (>300 m/day) allow rapid contaminant transport. These lower- and very-low-vulnerability zones had inland crystalline formations with deeper aquifers (>15 m) and lower conductivity (<5 m/day). Such findings concur with other coastal aquifer studies and thus certify recharge potential, soil texture, and aquifer media as critical controls governing contaminant migration. Validation against nitrate concentration data confirmed the predictive accuracy of the model. An ROC–AUC analysis indicated strong discrimination between contaminated (>10 mg/L NO_3^-) and uncontaminated sites. Specifically, the model achieved a sensitivity of 87.5% when high and very high vulnerability zones were combined, and a specificity of 75.0% when low and very low zones were grouped, resulting in an overall classification accuracy of 90%. With an ROC–AUC value of ~0.93, it clearly indicates that the model can quasi-certainly differentiate contamination risk levels. Most nitrate exceedances were observed in areas of high VI, thereby indicating that the fuzzy inference has mainly captured the real causes of groundwater contamination. This means that the model is suitable for urban coastal areas where hydrogeological variability and anthropogenic pressures combine in more intricate ways. The sensitivity analysis indicated model robustness. Perturbations of ±10% in any one of the parameters (D, R, T, or K) induced less than ±1% change in the mean VI values; therefore, one can say that the model is not dependent on any one of the input variables to incur meaningful changes. This suggests that the multi-criteria fuzzy approach tends to be less biased than those methods that entail significant reliance on weight assignments. From the management standpoint, the generated vulnerability map can provide valuable high-resolution decision-support tools for prioritising groundwater protection tasks. Other things that could be considered at this stage, based on the study outputs: areas identified to be at high vulnerability, especially those extending along the coastal belt and floodplains, could be subjected to very strict land use controls, treatment of wastewater, and perhaps the elimination of potential sources of nitrates from agricultural practices. In addition, given its flexibility, the model can be adapted for other coastal cities facing similar pressures on groundwater quality.

Conclusion

In this study, it has been found that a fuzzy logic-based approach works well and hence serves as a reliable method of assessing groundwater pollution vulnerability in the Chennai Metropolitan Region. The model produces a very detailed Vulnerability Index (VI) map, reflecting the region's real hydrogeological situation after having been provided with 7 important hydrogeological and land-related parameters: depth to the water table, net recharge, soil texture, aquifer media, hydraulic conductivity, slope, and land use/land cover. The vulnerability mapping indicates that high and very high hazard zones lie along the coastal belt, river floodplains, and areas densely built up. In these areas, shallow aquifers of very high permeability allow rapid transport of contaminants. Alternatively, the inland crystalline formations far from surface water bodies have deep groundwater with low hydraulic conductivity, indicating low vulnerability. The model was validated by comparing it with nitrate concentration data, which show most of the contamination hotspots to indeed fall under high-VI zones. Quantitatively, the model achieved a sensitivity of 87.5%, a specificity of 75.0%, and an overall classification accuracy of 90%, with an ROC–AUC of ~0.93, underscoring its strong discrimination capability. Sensitivity analyses have been conducted and found that no single parameter disproportionately influenced the results, reflecting the robustness of the multi-criteria fuzzy inference system. In perspective, this vulnerability map is an important tool for decision-making for the water resource managers and policymakers. It is capable of helping target the areas for interventions, including land-use regulations, wastewater management, and control of nitrate from agricultural sources. This approach is flexible and can easily be transferred to comparable coastal urban regions with groundwater quality threats.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Aller, L., Lehr, J. H., Petty, R., & Bennett, T. (1987). DRASTIC: a standardized system to evaluate groundwater pollution potential using hydrogeologic setting. *Journal Geological Society of India, 29*(1), 23-37. https://doi.org/10.17491/jgsi/1987/290112

Al-Rashidi, A., Sabarathinam, C., Samayamanthula, D. R., Alsabti, B., & Rashid, T. (2023). Groundwater management for agricultural purposes using fuzzy logic technique in an arid region. *Water*, *15*(14), 2674. https://doi.org/10.3390/w15142674

Amir, R. Y. A. (2023). Applying Multi-objective Geometric Programming to the Fuzzy Inventory of Kerosene in Al-Dora Refinery. *International Academic Journal of Social Sciences*, *10*(1), 9–17. https://doi.org/10.9756/IAJSS/V10I1/IAJSS1002

Barhoumi, E. M., & Charabi, Y. (2025). A Bidirectional Transformer Model for Rainfall-Runoff Prediction in Smart Drainage Systems. *International Academic Journal of Innovative Research*, *12*(1), 36–44. https://doi.org/10.71086/IAJIR/V12I1/IAJIR1207

Burrough, P. A., McDonnell, R. A., & Lloyd, C. D. (2015). *Principles of geographical information systems*. Oxford university press. 17-34

Caniani, D., Lioi, D. S., Mancini, I. M., Masi, S., & Sdao, F. (2011). Fuzzy logic model development for groundwater pollution risk assessment. *European Water*, *35*, 13-22.

Chauhan, O. (2024). Planning for Restoration and Rejuvenation of Water Bodies across Southern Ridge of South & Southeast Delhi.

Falih, K. T. (2024). An Assessment of Soil Metal Contamination in Oil Fields Utilising Petroleum Contamination Indices and GIS Methods. *International Academic Journal of Science and Engineering*, *11*(1), 265–276. https://doi.org/10.9756/IAJSE/V11I1/IAJSE1131

Gogu, R. C., & Dassargues, A. (2000). Current trends and future challenges in groundwater vulnerability assessment using overlay and index methods. *Environmental geology*, *39*(6), 549-559. https://doi.org/10.1007/s002540050466

Halder, S., Roy, M. B., Roy, P. K., & Sedighi, M. (2023). Groundwater vulnerability assessment for drinking water suitability using Fuzzy Shannon Entropy model in a semi-arid river basin. *Catena*, *229*, 107206. https://doi.org/10.1016/j.catena.2023.107206

Iqbal, J., Gorai, A. K., Katpatal, Y. B., & Pathak, G. (2014). Development of a GIS-based fuzzy pattern recognition model (modified DRASTIC model) for groundwater vulnerability to pollution assessment. *International Journal of Environmental Science and Technology*, *12*(10), 3161–3174. https://doi.org/10.1007/s13762-014-0693-x

Jegede, D. O., Afolabi, T. A., Agunbiade, F. O., Oladeji, O. S., Gbadamosi, M. R., Sojinu, S. O., ... & Varanusupakul, P. (2025). Fuzzy logic modelling of the pollution pattern of potentially toxic elements and naturally occurring radionuclide materials in quarry sites in Ogun State, Nigeria. *Environmental geochemistry and health*, *47*(2), 59. https://doi.org/10.1007/s10653-025-02359-2

Krishnamurthy, K. V., & Rajendran, N. (2025). Proceedings of the Annual General Meeting of the Geological Society of India–2025, Nainital, Uttarakhand. https://doi.org/10.17491/jgsi/2025/174313

Loganathan, S., & Sathiyamoorthy, M. (2024). Demarcation of groundwater potential zones in Ponnai sub-basin, Southern India using remote sensing, GIS and fuzzy-AHP approaches. *Water Supply*, *24*(5), 1529-1545. https://doi.org/10.2166/ws.2024.084

Makhlough, A., Nasrollahzadeh Saravi, H., Naderi, M. J., Eslami, F., & Ahmadnezhad, A. (2023). Use of algal indices for determining water quality in the Sirvan River tributaries (Kurdistan, Iran). *International Journal of Aquatic Research and Environmental Studies*, *3*(1), 43-56. https://doi.org/10.70102/IJARES/V3I1/5

MathWorks. (2025). *MATLAB Online* Version 25.1.0.2952844, (R2025a) Natick, Massachusetts. The MathWorks, Inc.

Mukherjee, A., & Panda, J. (2024). A study on the urban growth and dynamics over 16 major cities of India. *Journal of Earth System Science*, *133*(2), 66.

Nourani, V., Maleki, S., Najafi, H., & Baghanam, A. H. (2024). A fuzzy logic-based approach for groundwater vulnerability assessment. *Environmental Science and Pollution Research*, *31*(12), 18010-18029. https://doi.org/10.1007/s11356-023-26236-6

Radhakrishnan, S., Velanganni, R., & Paranthaman, P. (2024). Groundwater Management: Integrating Geological and hydrological data for effective decision making. *Archives for technical sciences*, *31*(2), 131-139. https://doi.org/10.70102/afts.2024.1631.131

Rajasekhar, M., Raju, G. S., Sreenivasulu, Y., & Raju, R. S. (2019). Delineation of groundwater potential zones in semi-arid region of Jilledubanderu river basin, Anantapur District, Andhra Pradesh, India using fuzzy logic, AHP and integrated fuzzy-AHP approaches. *HydroResearch*, *2*, 97-108. https://doi.org/10.1016/j.hydres.2019.11.006

Rangarajan, S., Thattai, D., Yellasiri, S. R. R., Vytla, R., Tedla, N., & Mandalemula, B. (2018). Detecting changes in annual and seasonal rainfall patterns for Chennai, India. *Journal of Hydrologic Engineering*, *23*(4), 05018001. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001630

Raufu, I. O. (2024). Evaluation of Different Digital Elevation Models (DEMs) for Geospatial Applications: A Case Study of Ibadan, Nigeria. *African Journal of Land Policy and Geospatial Sciences*, *7*(4), 1137-1154.

Tamil Nadu Pollution Control Board. (2023). *Water quality and industrial zoning data — Chennai*. Government of Tamil Nadu.

Thabit, H., Haider, H., Ghumman, A. R., Alattyih, W., Alodah, A., Hu, G., & Shafiquzzaman, M. (2023). Fuzzy-based human health risk assessment for shallow groundwater well users in Arid Regions. *Sustainability*, *15*(22), 15792. https://doi.org/10.3390/su152215792

Uricchio, V. F., Giordano, R., & Lopez, N. (2004). A fuzzy knowledge-based decision support system for groundwater pollution risk evaluation. *Journal of environmental management*, *73*(3), 189-197. https://doi.org/10.1016/j.jenvman.2004.06.011

Varshavardhini, S., & Rajesh, A. (2023). An Efficient Feature Subset Selection with Fuzzy Wavelet Neural Network for Data Mining in Big Data Environment. *Journal of Internet Services and Information Security*, *13*(2), 233-248. https://doi.org/10.58346/JISIS.2023.I2.015

Verma, N., & Reddy, A. (2025). The Demographic Consequences of Urbanisation: A Study of Changes in Family Structure and Household Composition. *Progression Journal of Human Demography and Anthropology*, *3*(1), 1-7.

World Health Organization. Water, Sanitation and Health Team (2004). Guidelines for drinking-water quality. Vol. 1, Recommendations, 3rd ed. World Health Organization. *World Health Organization*.

Ziwei, M., & Han, L. L. (2023). Scientometric Review of Sustainable Land Use and Management Research. *Aquatic Ecosystems and Environmental Frontiers*, *1*(1), 21-24.