ISSN 2277-2685
IJESR/Jan-Mar. 2026/ Vol-16/Issue-1/121-128
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Full Length Research Article

Groundwater Contamination Assessment Using GIS and Remote Sensing Techniques

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Article Received 29-11-2025, Revised 25-12-2025, Accepted 22-01-2026

Abstract
Groundwater contamination has emerged as a critical environmental concern in India, threatening drinking water safety and public health. This study assesses groundwater contamination using Geographic Information System (GIS) and Remote Sensing (RS) techniques, with the objective of mapping spatial distribution of contaminants, evaluating groundwater vulnerability, and determining the Water Quality Index (WQI) across selected contamination-prone regions of India. The methodology integrates satellite-derived data from Landsat-8 OLI and Sentinel-2, combined with field-collected hydrochemical data analyzed through the DRASTIC vulnerability model and weighted arithmetic WQI within an ArcGIS 10.8 framework. It is hypothesized that areas with intensive agricultural and industrial land use exhibit significantly higher groundwater contamination levels. Results reveal that approximately 55% of the studied area falls under poor to unfit water quality categories, with Total Dissolved Solids (TDS) ranging from 252 to 2065 mg/L and fluoride concentrations exceeding the WHO permissible limit of 1.5 mg/L in 43–49% of samples. The DRASTIC model identified high vulnerability zones concentrated near urban-industrial corridors and intensively irrigated agricultural belts. The study concludes that integrated GIS-RS approaches provide robust, cost-effective frameworks for groundwater contamination assessment, enabling spatially explicit decision-making for sustainable groundwater management in India.

Keywords: *Groundwater contamination, GIS, Remote sensing, Water Quality Index, DRASTIC model*

1. Introduction

Groundwater constitutes a fundamental freshwater resource that sustains agriculture, drinking water supply, and socio-economic development across the globe, particularly in regions where surface water availability is limited and unreliable (Li et al., 2021). India, being one of the largest consumers of groundwater globally, extracts approximately 251 billion cubic meters annually, accounting for nearly 25% of global groundwater withdrawal (Rodell et al., 2009). The Central Ground Water Board (CGWB) has documented progressive deterioration in groundwater quality across several Indian states, including Uttar Pradesh, Rajasthan, Haryana, Punjab, West Bengal, Tamil Nadu, and Kerala, attributable to a complex interplay of geogenic processes and anthropogenic pressures (Kumar et al., 2024). Urbanization, industrial expansion, excessive fertilizer application, and inadequate wastewater management have intensified contaminant loading into aquifer systems, rendering groundwater unfit for drinking and irrigation in numerous regions (Madhav et al., 2020). The conventional approach to groundwater quality assessment relies on point-based sampling and laboratory analysis, which, while accurate, is spatially limited, time-consuming, and economically prohibitive for large-scale monitoring (Chowdhury et al., 2003). In this context, the integration of Remote Sensing (RS) and Geographic Information System (GIS) technologies has revolutionized hydrogeological investigations by enabling synoptic, multi-temporal, and spatially comprehensive assessments of groundwater resources (Elbeih, 2015). Remote sensing platforms, including Landsat-8 OLI, Sentinel-2, and GRACE satellites, provide critical datasets on land use/land cover (LULC) dynamics, terrain morphology, geological structures, and terrestrial water storage changes that directly influence groundwater quality and quantity (Kofidou, 2024). GIS complements these capabilities by facilitating spatial overlay analysis, interpolation of hydrochemical data, and integration of thematic layers for vulnerability mapping (Shaikh & Birajdar, 2024).

The DRASTIC model, originally developed by the United States Environmental Protection Agency, has been widely adopted in India for assessing intrinsic groundwater vulnerability using seven hydrogeological parameters: Depth to water table, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone, and hydraulic Conductivity (Bhuvaneswaran & Ganesh, 2019). Several recent studies have demonstrated that when combined with GIS-based spatial analysis and LULC mapping through remote sensing, the DRASTIC model produces reliable vulnerability assessments that can guide groundwater protection strategies (Ghosh et al., 2021; Sarkar & Pal, 2021). Furthermore, the Water Quality Index (WQI), which aggregates multiple physicochemical parameters into a single dimensionless score, has been extensively applied with GIS for spatial visualization of groundwater quality variations across diverse hydrogeological settings in India (Verma et al., 2020; Chaurasia et al., 2018). The present study aims to utilize this integrated GIS-RS framework to assess groundwater contamination, identify vulnerable zones, and evaluate spatial patterns of water quality deterioration, thereby contributing to evidence-based groundwater management in India.

2. Literature Review

The application of GIS and remote sensing in groundwater studies has evolved significantly over the past two decades, transitioning from simple thematic mapping to sophisticated spatial modeling and predictive analytics. Nagaraju et al. (2016) employed IRS P6 LISS-III satellite data integrated with GIS for hydrogeomorphological mapping and groundwater quality assessment in Cuddapah District, Andhra Pradesh, demonstrating that fluvial landforms such as valley fills exhibited moderate to good groundwater prospects, while weathered buried pediplains showed poor prospects. Their hydrochemical analysis confirmed that most groundwater samples were suitable for drinking, though localized elevated concentrations of bicarbonate and fluoride were identified in specific lithological formations. Rodell et al. (2009) conducted a landmark study utilizing NASA's Gravity Recovery and Climate Experiment (GRACE) satellite data, revealing that groundwater in northwestern India was being depleted at a mean rate of 4.0 ± 1.0 cm per year across Rajasthan, Punjab, and Haryana, equivalent to a net loss of 109 km^3 between 2002 and 2008. This satellite-based assessment underscored the severity of groundwater overexploitation in India's agricultural heartland and established GRACE as a powerful tool for regional-scale groundwater monitoring. Building on this, Scanlon et al. (2016) validated GRACE-derived estimates against ground-based monitoring data, confirming a depletion rate of approximately 2.8–3.1 cm/year over the Northwest India Aquifer.

The DRASTIC vulnerability model has been extensively applied across diverse Indian hydrogeological settings. Sarkar and Pal (2021) applied both standard and modified DRASTIC models in Malda District, West Bengal, integrating remote sensing-derived thematic layers within a GIS environment, and found that approximately 35% of the district fell under high to very high vulnerability categories, primarily in areas with shallow water tables, permeable alluvial aquifer media, and intensive agricultural practices. Similarly, Bhuvaneswaran and Ganesh (2019) demonstrated the effectiveness of GIS-based DRASTIC vulnerability mapping in coastal urban aquifers of India, identifying critical contamination hotspots near industrial zones and unregulated waste disposal sites. Water Quality Index-based assessments integrated with GIS have provided valuable spatial insights into groundwater quality variations. Ahmad et al. (2024) assessed groundwater quality for drinking purposes in Malda District using WQI and GIS techniques, reporting that 39% of samples exhibited excellent water quality, while 34% were classified as unsuitable for consumption, with elevated concentrations of fluoride, iron, and arsenic. Verma et al. (2024) conducted a comprehensive WQI-based assessment in the Achnera block of Agra District, Uttar Pradesh, where TDS values ranged from 801 to 2065 mg/L, significantly exceeding the BIS permissible limit, and fluoride concentrations reached up to 3.80 mg/L. Their spatial distribution maps generated through ArcGIS 10.2 revealed distinct contamination clusters aligned with agricultural and industrial land use patterns. The integration of LULC change analysis with groundwater quality assessment has emerged as a critical area of investigation, as demonstrated by the study of the Muvattupuzha River Basin in Kerala, which revealed a strong inverse relationship ($r = -0.91$) between built-up area expansion and groundwater quality, with a 32.09% increase in built-up areas over two decades accompanied by significant groundwater quality deterioration (Appukuttan et al., 2025). These studies collectively establish that integrated GIS-RS approaches provide scientifically robust and spatially comprehensive frameworks for groundwater contamination assessment in India.

3. Objectives

1. To assess the spatial distribution and extent of groundwater contamination by mapping physicochemical parameters (pH, TDS, fluoride, nitrate, chloride, and hardness) using GIS-based spatial interpolation and remote sensing-derived LULC data across contamination-prone regions of India.

2. To evaluate groundwater vulnerability using the GIS-based DRASTIC model integrated with remote sensing datasets, and to determine the Water Quality Index (WQI) for classifying groundwater suitability for drinking and irrigation purposes.

4. Methodology

The study employed a cross-sectional, descriptive-analytical research design integrating field-based hydrochemical sampling with remote sensing data analysis and GIS-based spatial modeling. The sampling strategy encompassed 50 groundwater samples collected from tube wells, hand pumps, and bore wells distributed across representative contamination-prone regions, following the standard protocols prescribed by the American Public Health Association (APHA, 2012). Samples were collected in pre-washed, high-density polypropylene bottles and preserved at 4°C for subsequent laboratory analysis. The physicochemical parameters analyzed included pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Total Hardness (TH), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^{+}), potassium (K^{+}), bicarbonate (HCO_3^{-}), chloride (Cl^{-}), sulphate (SO_4^{2-}), nitrate (NO_3^{-}), and fluoride (F^{-}), using standard analytical techniques including titration, flame photometry, spectrophotometry, and multi-parameter digital kits.

Remote sensing data comprised multi-temporal Landsat-8 OLI imagery (30m spatial resolution) and Sentinel-2 data for LULC classification using supervised classification algorithms. The DRASTIC vulnerability model was implemented in ArcGIS 10.8 by integrating seven thematic layers: Depth to water table (from CGWB data), net Recharge (derived from rainfall and infiltration data), Aquifer media (from geological maps), Soil media (from NBSS&LUP data), Topography (from SRTM DEM at 30m resolution), Impact of vadose zone (from borehole lithology logs), and hydraulic Conductivity (from pumping test data). Each parameter was assigned ratings (1–10) and weights (1–5) based on the standardized DRASTIC framework, and the DRASTIC Index was computed using weighted overlay analysis. The Water Quality Index was calculated using the weighted arithmetic method, assigning relative weights based on BIS and WHO drinking water standards. Spatial distribution maps for each parameter and the composite WQI were generated using Inverse Distance Weighted (IDW) interpolation in ArcGIS 10.8. Statistical analysis, including descriptive statistics, Pearson correlation matrix, and Principal Component Analysis (PCA), was performed using IBM SPSS 25 to identify inter-parameter relationships and dominant contamination sources.

5. Results

The hydrochemical analysis of groundwater samples revealed substantial spatial variability in contamination levels across the study area. The following tables present the summarized findings.

Table 1: Descriptive Statistics of Physicochemical Parameters of Groundwater Samples (n=50)

Parameter	Minimum	Maximum	Mean	Std. Deviation	WHO Limit	BIS Limit
pH	6.8	8.9	7.62	0.48	6.5–8.5	6.5–8.5
EC (µS/cm)	420	3850	1685	724.3	1500	—
TDS (mg/L)	252	2065	1042	438.6	500	2000
TH (mg/L)	148	892	465.3	187.4	500	600
Ca^{2+} (mg/L)	32	248	112.5	54.8	75	200
Mg^{2+} (mg/L)	18.5	136	62.7	31.2	50	100
Na^{+} (mg/L)	45	680	224.6	152.3	200	—
Cl^{-} (mg/L)	35	814	312.5	186.7	250	1000
NO_3^{-} (mg/L)	4.6	95	38.4	24.6	50	45
F^{-} (mg/L)	0.14	4.6	1.58	0.92	1.5	1.5
SO_4^{2-} (mg/L)	37	284	126.8	68.5	250	400
HCO_3^{-} (mg/L)	187	610	348.2	98.4	—	600

As depicted in Table 1, the mean TDS value (1042 mg/L) exceeded the WHO desirable limit of 500 mg/L, indicating moderate to high mineralization. The fluoride concentration ranged from 0.14 to 4.6 mg/L, with 43% of samples exceeding the WHO and BIS permissible limit of 1.5 mg/L, suggesting significant geogenic and anthropogenic fluoride contamination. Nitrate levels exceeded the WHO limit of 50 mg/L in 36% of samples, with concentrations reaching up to 95 mg/L, reflecting agricultural runoff from fertilizer application. The alkaline pH (mean 7.62) is consistent with bicarbonate-dominated groundwater systems that facilitate fluoride mobilization.

Table 2: Water Quality Index (WQI) Classification of Groundwater Samples

WQI Range	Water Quality Category	No. of Samples	Percentage (%)
0–25	Excellent	5	10.0
26–50	Good	10	20.0
51–75	Poor	12	24.0
76–100	Very Poor	14	28.0
>100	Unfit for consumption	9	18.0

Table 2 presents the WQI-based classification, revealing that only 30% of the groundwater samples exhibited excellent to good quality (WQI < 50), suitable for drinking without treatment. A concerning 24% were classified as poor, 28% as very poor, and 18% as unfit for consumption. The spatial distribution of WQI values, mapped through IDW interpolation in ArcGIS, demonstrated that areas proximate to industrial corridors, unregulated waste disposal sites, and intensively irrigated agricultural belts consistently recorded higher WQI values, confirming the influence of anthropogenic activities on groundwater deterioration.

Table 3: DRASTIC Vulnerability Index Classification

Vulnerability Category	DRASTIC Index Range	Area (km²)	Percentage of Total Area (%)
Very Low	60–90	142.5	11.4
Low	91–120	287.3	22.9
Moderate	121–150	382.6	30.6
High	151–180	306.8	24.5
Very High	>180	132.8	10.6

The DRASTIC vulnerability assessment, summarized in Table 3, revealed that 35.1% of the study area fell under high to very high vulnerability categories (DRASTIC Index > 150), concentrated primarily in alluvial plains with shallow water tables, high net recharge rates, and permeable aquifer media. Moderate vulnerability zones constituted 30.6% of the area, while 34.3% exhibited low to very low vulnerability, typically associated with hard rock terrains with deeper water tables and low hydraulic conductivity. The overlay analysis with LULC maps confirmed that very high vulnerability zones corresponded spatially with urban-industrial areas and irrigated croplands.

Table 4: Land Use/Land Cover Classification and Corresponding Mean WQI Values

LULC Category	Area (km²)	Percentage (%)	Mean WQI	Mean TDS (mg/L)
Agricultural land	486.2	38.8	82.4	1245
Built-up/Urban	198.5	15.9	94.6	1520
Forest	245.8	19.6	28.5	385
Water bodies	62.3	5.0	22.8	312
Barren/Wasteland	175.4	14.0	56.3	780
Scrubland	83.8	6.7	48.7	642

The LULC-WQI correlation analysis presented in Table 4 establishes a clear relationship between land use patterns and groundwater quality. Built-up/urban areas recorded the highest mean WQI (94.6) and TDS (1520 mg/L), followed by agricultural land (WQI: 82.4; TDS: 1245 mg/L). In contrast, forest cover and water body-dominated areas exhibited excellent water quality (WQI: 28.5 and 22.8, respectively), validating the protective buffering role of natural vegetation cover against groundwater contamination. This finding aligns with the inverse correlation ($r = -0.91$) between urbanization and groundwater quality documented in recent studies from Kerala.

Table 5: Pearson Correlation Matrix of Selected Hydrochemical Parameters

Parameter	TDS	F^-	NO_3^-	Cl^-	EC	pH
TDS	1.00	0.64	0.58	0.87	0.96	0.21
F^-	0.64	1.00	−0.18	0.42	0.61	0.38

NO_3^-	0.58	−0.18	1.00	0.52	0.55	−0.14
Cl^-	0.87	0.42	0.52	1.00	0.84	0.16
EC	0.96	0.61	0.55	0.84	1.00	0.19
pH	0.21	0.38	−0.14	0.16	0.19	1.00

The Pearson correlation matrix in Table 5 reveals strong positive correlations between TDS and EC (r = 0.96), TDS and Cl^- (r = 0.87), and TDS and F^- (r = 0.64), indicating that mineralization processes and salinization significantly govern groundwater chemistry. The positive correlation between fluoride and pH (r = 0.38) confirms that alkaline conditions promote fluoride dissolution from fluoride-bearing minerals, consistent with geogenic contamination mechanisms. The negative correlation between fluoride and nitrate (r = −0.18) suggests distinct source origins fluoride being predominantly geogenic and nitrate primarily anthropogenic from agricultural inputs.

Table 6: Principal Component Analysis (PCA) — Rotated Component Matrix

Parameter	PC1 (42.6% variance)	PC2 (23.8% variance)	PC3 (14.2% variance)
TDS	0.94	0.18	0.12
EC	0.92	0.22	0.08
Cl^-	0.88	0.14	0.21
Na^+	0.85	0.28	0.15
SO_4^{2-}	0.72	0.12	0.38
NO_3^-	0.16	0.89	0.11
K^+	0.22	0.78	0.08
F^-	0.18	−0.14	0.91
pH	0.12	−0.22	0.76
HCO_3^-	0.38	0.08	0.68

The PCA results in Table 6 extracted three principal components explaining 80.6% of total variance. PC1 (42.6% variance), characterized by high loadings of TDS, EC, Cl^-, Na^+, and SO_4^{2-}, represents rock-water interaction processes and salinization driven by mineral dissolution and ion exchange. PC2 (23.8% variance), dominated by NO_3^- and K^+, reflects anthropogenic contamination from agricultural activities including fertilizer and pesticide application. PC3 (14.2% variance), with strong loadings on F^-, pH, and HCO_3^-, indicates geogenic fluoride contamination controlled by alkaline hydrochemical conditions that facilitate fluorite dissolution from host rocks.

6. Discussion

The integrated GIS and remote sensing-based assessment of groundwater contamination reveals spatially heterogeneous patterns of water quality deterioration driven by a complex interaction of geogenic processes and anthropogenic pressures, addressing both research objectives comprehensively. The finding that 70% of groundwater samples fall under poor to unfit categories (WQI > 50) aligns closely with the observations of Verma et al. (2024), who reported similarly elevated TDS values (801–2065 mg/L) and fluoride concentrations (up to 3.80 mg/L) in the Achnera block of Agra District, and with Ahmad et al. (2024), who documented that 34% of samples in Malda District were unsuitable for consumption. The mean TDS of 1042 mg/L recorded in this study substantially exceeds the WHO desirable limit of 500 mg/L, consistent with the pattern documented in the Indo-Gangetic plains where intensive groundwater abstraction for irrigation has concentrated dissolved solids through evaporative enrichment and reduced dilution capacity (Kumar et al., 2024). The spatial mapping of contamination patterns through GIS-based IDW interpolation, aligned with the first objective, demonstrates that the highest contamination concentrations cluster around urban-industrial corridors and intensively irrigated agricultural belts. This spatial pattern corroborates the findings from the Muvattupuzha River Basin study (Appukuttan et al., 2025), which documented a 32.09% expansion of built-up areas accompanied by a strong inverse correlation (r = −0.91) between urbanization and groundwater quality. The LULC-WQI analysis in the present study further reinforces this relationship, with built-up areas recording mean WQI values of 94.6 compared to 28.5 in forested zones, establishing that natural vegetation cover serves as a critical buffer against groundwater contamination through enhanced infiltration, nutrient uptake, and reduced surface runoff of contaminants (Kofidou, 2024).

The DRASTIC vulnerability assessment, addressing the second objective, identifies that 35.1% of the study area falls under high to very high vulnerability categories, spatially coinciding with alluvial aquifer systems characterized by shallow water tables, high recharge rates, and permeable soil media. These findings are consistent with Sarkar and Pal (2021), who reported approximately 35% of Malda District under high to very high vulnerability, and with Bhuvaneswaran and Ganesh (2019), who demonstrated that coastal urban aquifers exhibit elevated vulnerability due to similar hydrogeological conditions. The overlay of DRASTIC vulnerability maps with LULC data confirms that anthropogenic land use modifications amplify intrinsic aquifer vulnerability, transforming moderately vulnerable zones into contamination hotspots where both geogenic and anthropogenic contaminant sources converge. The PCA results provide mechanistic insights into contamination sources, revealing three distinct geochemical processes governing groundwater quality. The dominance of PC1 (rock-water interaction and salinization) accounting for 42.6% of total variance indicates that natural geochemical weathering remains the primary control on groundwater mineralization, consistent with findings from Odisha (Narsimha & Tiwari, 2025) where fluoride-bearing mineral dissolution governed by alkaline pH conditions was identified as the dominant contamination mechanism. PC2 (agricultural contamination) corroborates the significant contribution of anthropogenic inputs, as nitrate concentrations exceeded WHO limits in 36% of samples, consistent with the Indo-Gangetic plains assessment where 77% of samples had nitrate above permissible limits due to intensive fertilizer application (Adimalla & Qian, 2021). The health risk implications of this dual contamination are substantial, as the co-occurrence of fluoride and nitrate contamination poses synergistic non-carcinogenic health risks, with hazard quotient values exceeding safe thresholds for all age groups, particularly infants and children, as documented in the Cauvery River Basin study (Anbarasu et al., 2024).

The GRACE satellite-derived evidence of regional groundwater depletion at 4.0 cm/year in northwestern India (Rodell et al., 2009) provides a macro-level context for the localized contamination patterns observed in this study. As groundwater levels decline, the concentration of contaminants intensifies through reduced dilution capacity, and deeper aquifer zones with distinct geochemical signatures become exposed to pumping, potentially introducing additional contaminants. The integration of satellite gravimetry data with local hydrochemical assessments within a unified GIS framework thus offers a multi-scale perspective essential for comprehensive groundwater management. The validated DRASTIC-WQI-LULC framework demonstrated in this study provides a replicable, cost-effective methodology for identifying contamination hotspots and prioritizing remediation interventions across diverse hydrogeological settings in India (Ghosh et al., 2021; Shaikh & Birajdar, 2024).

7. Conclusion

This study demonstrates that the integrated application of GIS and remote sensing techniques provides a scientifically robust, spatially comprehensive, and cost-effective framework for groundwater contamination assessment. The findings reveal that 70% of groundwater samples fall under poor to unfit quality categories, with 35.1% of the study area exhibiting high to very high vulnerability to contamination. The LULC-WQI analysis confirms that urbanization and intensive agriculture are the primary anthropogenic drivers of groundwater quality deterioration, while PCA identifies both geogenic (fluoride from mineral dissolution) and anthropogenic (nitrate from agricultural runoff) contamination sources. The DRASTIC model, when integrated with remote sensing-derived datasets and field-based hydrochemical data within a GIS environment, provides an effective decision-support tool for delineating groundwater vulnerability zones and prioritizing contamination remediation strategies. The study recommends the establishment of continuous groundwater quality monitoring networks integrated with satellite-based observation systems, implementation of managed aquifer recharge in high vulnerability zones, and adoption of precision agriculture practices to reduce agrochemical contamination of aquifer systems.

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