

Geospatial Methods for SDG-Aligned Land and Water Resource Management: A Bibliometric and Systematic Review of Research Trends (2021–2026)

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Geospatial Methods for SDG-Aligned Land and Water Resource Management: A Bibliometric and Systematic Review of Research Trends (2021–2026).

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Abstract

Geospatial methods have become indispensable for sustainable land and water resource management under growing pressures from climate change, urbanization, and water scarcity. This study maps global research trends in geospatial methods for land and water resource management, evaluates the comparative performance of dominant analytical frameworks, and identifies critical methodological gaps and future research priorities. A bibliometric analysis of 335 peer-reviewed articles (2021–2026, Dimensions API) was combined with a PRISMA-based systematic review of 59 studies drawn from Scopus, PubMed, and Dimensions AI. Publication output grew by 59.2% between 2021 and 2025, peaking at 1,735 articles in 2025, driven by post-COVID remote monitoring demand and the mainstreaming of cloud-based geospatial platforms. China and the United States dominated output and collaboration, while Kenya, Ecuador, and South Africa achieved disproportionately high citation impact, reflecting the research value of studies addressing acute resource stress. Groundwater potential mapping was the most studied application (39% of the corpus), with the Analytical Hierarchy Process (AHP) being the most widely applied method despite machine learning consistently outperforming it in within-study comparisons (mean ROC-AUC: 0.860 vs. 0.748). Meta-regression revealed that model accuracy is poorly predicted by the number of thematic input layers ($R^2=0.094$), challenging the assumption that more input data produces better models. Furthermore, 92% of comparative studies confirmed that urban and agricultural land expansion measurably reduces groundwater levels or water body extent, providing strong directional evidence for SDG 6 and SDG 15 monitoring. Despite these advances, many studies rely on static datasets and single-site case studies, with limited attention paid to real-time monitoring, policy integration, and large-scale validation. The review identifies real-time monitoring, Explainable AI, and climate-resilient geospatial frameworks as the three most critical priorities for advancing policy-relevant and reproducible geospatial science.

Keywords: Geospatial technologies, land management, remote sensing, spatial data science, water resources management.

1. Introduction

The interconnection between land and water resources is fundamental to sustainable development because it sustains both ecological balance and human well-being (Tudose et al., 2023). Modifications in land use can significantly influence hydrological processes and ecosystem services, highlighting the need for a clear and integrated understanding of land and water interactions for effective resource management (Jin et al., 2015). Whereas some studies emphasize economic mechanisms such as payment for ecosystem services and conservation incentive schemes (Petrochenko & Petrochenko, 2021), others regard integrated ecosystem service valuation as the primary decision-support framework (Liu et al., 2013). In contrast, incorporating water management measures into land-use planning has been seen as a means of enhancing ecological health (Kalogiannidis et al., 2023). However, challenges remain in implementing these integrated approaches in diverse geographical and socioeconomic circumstances (Naghiloo, 2023).

Geospatial technologies provide a strong foundation for integrated land and water resource management by enabling effective observation, analysis, and decision-making at multiple scales. Remote sensing offers multi-temporal data for monitoring land–water processes, whereas Geographic Information Systems (GIS) integrate diverse datasets for spatial analysis and scenario evaluation. In addition, GNSS/GPS technologies support accurate geolocation, thereby improving the reliability and reproducibility of geospatial analyses. In groundwater research, remote sensing and GIS techniques are widely used to identify potential zones by integrating factors such as geology, geomorphology, drainage, soil, slope, rainfall, and land use/land cover. Recent advancements, including satellite gravimetry and optical–SAR data fusion, have enabled cost-effective and non-invasive estimation of groundwater storage dynamics, complementing traditional field-based approaches (Ibrahim et al., 2024). Web-GIS platforms reduce operational costs by enabling remote data curation, real-time visualization, and collaborative stakeholder interpretation, making geospatial monitoring more accessible to resource-constrained agencies (Wu et al., 2022). Recent studies in urban and dryland settings suggest that incorporating climate-smart soil–water methods into Integrated Water Resource Management (IWRM) can improve resilience, though uptake depends on governance capacity and local institutional fit (Jat et al., 2025).

Previous reviews of geospatial applications in land and water management have predominantly adopted either a domain-specific scope focusing on individual applications such as groundwater mapping (Ibrahim et al., 2024) or LULC change detection (Gadal &

Mozgeris, 2025) or a single-method framework without cross-domain synthesis. No prior study has combined bibliometric analysis with a PRISMA-based systematic review and meta-regression of study design parameters to quantitatively assess what drives model performance differences across geospatial studies during the post-AI, post-COVID acceleration period of 2021–2026. This study addresses three specific gaps: (1) the absence of a bibliometric characterization of the 2021–2026 geospatial research landscape for land and water management; (2) the lack of a quantitative analysis of how study design choices influence model accuracy; and (3) the absence of a geographic mapping of method–performance disparities that could guide where ML deployment would deliver the greatest benefit. The novelty of this study lies in three contributions. First, it is the first systematic review to combine bibliometric analysis with PRISMA-based meta-regression specifically for geospatial methods in land and water resource management during the 2021–2026 period. Second, it introduces a quantitative meta-regression framework demonstrating that commonly reported study design parameters (layer count, validation point count) are weak predictors of model accuracy. Third, it proposes a five-dimension quality appraisal tool adapted from clinical frameworks, providing the first standardized scoring rubric for geospatial systematic reviews. The paper is organized as follows: Section 2 describes the methodology; Section 3 presents bibliometric results, regression analysis, quality assessment, and thematic findings; Section 4 discusses implications, challenges, research gaps, and future directions; and Section 5 concludes with five data-anchored findings and three priority recommendations.

2. Methodology

2.1 Bibliometric analysis

2.1.1 Data sources and database selection

Bibliometric data were obtained from the Dimensions API (Digital Science, London, UK), selected as the primary data source based on three criteria: (i) breadth of coverage Dimensions indexes more than 140 million publications across all disciplines, including grey literature, preprints, and open-access repositories, offering a broader scope than either Scopus or Web of Science (WoS) for a multidisciplinary geospatial topic; (ii) open-access metadata full bibliometric metadata are freely available without institutional subscription, ensuring the reproducibility of the dataset construction for researchers without access to proprietary databases; and (iii) programmatic API access the Dimensions API supports bulk record

retrieval via scripted queries, enabling transparent and automated dataset construction that eliminates manual download errors (Table 1).

To validate the representativeness of the Dimensions-based dataset, cross-validation was conducted against both Scopus and WoS following a two-step protocol. In the first step, a stratified random subsample of 200 records (60% of the final corpus of $n = 335$) was drawn from the Dimensions dataset and cross-checked against Scopus; 94% ($n = 188$) of the sampled records were identified in Scopus with fully matching bibliographic metadata (title, authors, DOI, and publication year), confirming high cross-database overlap. In the second step, the ten most productive countries identified in the Dimensions co-authorship analysis China, the United States, India, Italy, Germany, the United Kingdom, Australia, Pakistan, Ethiopia, and Nigeria were compared against equivalent country-level publication rankings generated independently from Scopus and WoS for the identical search string and study period. Spearman rank correlations of $\rho = 0.92$ (Dimensions vs. Scopus) and $\rho = 0.89$ (Dimensions vs. WoS) were obtained, both indicating a strong concordance ($p < 0.01$). These results confirm that the Dimensions -based analytical findings are representative of the broader indexed literature and support the use of Dimensions as the primary data source for this review.

The full bibliometric integration of all three databases simultaneously treating each as an equal primary source and merging the resulting datasets was not pursued for three methodological reasons. First, Scopus and WoS require institutional subscriptions that preclude free programmatic bulk access, limiting the reproducibility of a multi-database approach for readers without institutional affiliation. Second, merging records from three databases with different indexing scopes, metadata standards, and deduplication algorithms introduces systematic biases that cannot be reliably corrected without a validated cross-database merge protocol (Visser et al., 2021). Third, within bibliometric research, the cross-validation of a representative random subsample is widely accepted as a methodologically sound alternative to full database integration when primary source selection is justified on independent grounds. This approach is consistent with published bibliometric methodology guidelines, which accept cross-validation of a representative subsample as methodologically sound (Zupic & Čater, 2015; Donthu et al., 2021). The cross-validation results reported above satisfy this criterion.

2.1.2 Search strategy and data filtering pipeline

The literature search was conducted on March 26, 2026, using the Boolean search string "*Geospatial Methods AND Land AND Water Resource Management*," applied to the title and

abstract fields of the Dimensions API. This string was designed to retrieve studies at the intersection of geospatial methodology and the management of land or water resources, two domains that are frequently co-addressed in the reviewed literature but rarely captured by a single topical key word. The initial search returned 7,104 records spanning all document types, publication years, and languages (Step 1, Table 2).

The dataset was refined using two sequential filters. In Step 2, a document-type restriction ("Article" only) was applied to exclude non-primary research outputs, including conference papers ($n \approx 2,100$), systematic and narrative reviews ($n \approx 1,200$), book chapters ($n \approx 800$), and editorials ($n \approx 500$), in combination with a publication-year restriction (2021–2026), reducing the dataset to 2,500 records. In Step 3, a language filter (English only) was applied, excluding 2,165 non-English articles (86.6% of the 2,500-record intermediate dataset); the high proportion of non-English records is attributable to Dimensions' comparatively broader indexing of Chinese, Arabic, and Spanish-language journals relative to Scopus or WoS. The final analytical corpus comprised 335 English-language peer-reviewed articles published between 2021 and 2026. The three publication counts cited in this study 7,104, 2,500, and 335 represent the sequential stages of this filtering pipeline (Table 2, Fig.1); all bibliometric analyses are derived exclusively from the final corpus of $n = 335$ unless explicitly stated otherwise.

The 2021–2026 study window was deliberately defined to capture a period of accelerated methodological transformation in geospatial sciences. Three interrelated justifications support this scope. First, the post-COVID-19 acceleration in geospatial research: The period following 2020 saw a marked increase in remote monitoring applications as field-survey-based data collection was disrupted by pandemic-related restrictions, driving rapid innovation in satellite-derived environmental monitoring (Mehmood et al., 2022). Second, alignment with the SDG implementation cycle: The 2021–2026 period falls within the second implementation phase of the United Nations Sustainable Development Goals (2016–2030), during which geospatial evidence became increasingly embedded in national SDG progress reporting, elevating the demand for reproducible, scalable geospatial frameworks (UN-GGIM, 2023). Third, the mainstreaming of deep learning in remote sensing: The period from approximately 2020 onward is widely identified as the inflection point at which convolutional neural networks, transformer architectures, and cloud-based processing platforms (e.g., Google Earth Engine) transitioned from experimental to mainstream adoption in geospatial analyses (Zhu et al., 2017). A broader baseline analysis spanning 2000–2020 would enable two-phase

historical versus recent trend comparisons; however, this is beyond the scope of the present study and is recommended as a priority for future work.

It is important to note that the 2026 data represent a partial year: the search was conducted on March 26, 2026, meaning that the 2026 publication count ($n = 249$) reflects approximately three months of output (January–March 2026) and cannot be directly compared with full-year counts for 2021–2025. Accordingly, Fig. 2 for 2026 is reported for transparency but is excluded from all year-on-year growth calculations; the trend analyses in this study are based exclusively on full-year data for 2021–2025 (Table 3).

2.1.3 Analytical tools and publication trend analysis

Analytical processing was conducted using two complementary software platforms: Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) was used for trend analysis, citation frequency tabulation, annual publication count aggregation, and year-on-year growth calculations. VOSviewer (version 1.6.20; van Eck & Waltman, 2010) was used for keyword co-occurrence network mapping and co-authorship network visualization, with a minimum keyword co-occurrence threshold of five and a minimum co-authorship link strength of two, applied to ensure network parsimony and interpretability. Country collaboration (co-authorship linkage), country citation patterns, and network centrality analyses were additionally performed using the integrated visualization tools within the Dimensions AI platform, leveraging its pre-computed collaboration indices for the filtered dataset.

The annual publication trends for 2021–2026 are presented in Table 3. Annual publication counts represent a cumulative growth of +59.2% over the five-year period (2021–2025). A minor consolidation dip was observed in 2023 ($n = 1,276$; -7.4% relative to 2022), followed by a recovery in 2024 ($n = 1,376$; $+7.8\%$) and a substantial surge in 2025, coinciding with the broad adoption of AI- and cloud-based geospatial workflows. The partial-year 2026 count ($n = 249$, January–March only) is consistent with an annualized projection of approximately 1,000 publications, suggesting a continuation of the post-2024 growth trajectory; however, this projection is speculative and should not be interpreted as a confirmed trend.

2.2 Systematic review methodology

This systematic review was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. This systematic

review was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

2.2.1 Literature search strategy

A comprehensive and systematic literature search was conducted on 26 March 2026 across three independent bibliographic databases: Scopus (n = 278 records), PubMed (n = 68 records), and Dimensions AI (n = 237 records), yielding a total of 583 documents identified across all sources prior to deduplication. The Dimensions AI database was selected as the primary bibliometric data source in preference to Scopus because of its broader multidisciplinary indexing, unrestricted open-access metadata, and programmatic API access, which enabled the reproducible bulk retrieval of bibliometric records. Cross-validation of a randomly selected subsample of 200 records confirmed a 94% overlap between Dimensions and equivalent Scopus records, supporting the reliability of this source substitution. PubMed was included to capture the biomedical and environmental health dimensions of water resource studies that may be under-indexed in Scopus and Dimensions.

The Boolean search string applied uniformly across all three databases was as follows:

*("Geospatial Methods" OR "GIS" OR "Remote Sensing" OR "Spatial Analysis")
AND ("Land Management" OR "Land Use" OR "Land Cover") AND ("Water
Resource Management" OR "Groundwater" OR "Hydrology" OR "Water
Quality")*

The search was applied to the title and abstract fields only to ensure specificity and reduce off-topic retrieval. No restrictions were applied to the geographic region or study design type during the search stage; all filtering was implemented through the staged inclusion and exclusion criteria described in Section 2.2. The search was not registered prospectively; the authors acknowledge this as a limitation and recommend that future iterations of this review adopt the PROSPERO or OSF registration protocol.

2.2.2 Inclusion and exclusion criteria

Eligibility was determined by applying pre-specified inclusion and exclusion criteria across eight categories (Table 4). These criteria were established prior to the screening phase and applied consistently by two independent reviewers; discrepancies were resolved by a consensus discussion. The criteria were designed to restrict the corpus to empirical geospatial studies with a direct and demonstrable application to land or water resource management published in English within the 2021–2026 study window.

2.2.3 Screening process

The 583 records identified across the three databases were imported into a shared spreadsheet and deduplicated using a two-pass protocol: automated deduplication based on DOI matching (pass 1), followed by manual title-and-author string comparison for records without DOIs (pass 2). This process identified 257 duplicate records, yielding 326 unique records for screening, as illustrated in the PRISMA 2020 flow diagram (Fig. 8). All 325 records were screened at the title and abstract levels by two independent reviewers applying the Stage 1 and Stage 2 criteria specified in Table 4. Following title and abstract screening, 325 records were excluded (190 as off-topic, 89 as conference abstracts or non-peer-reviewed, 29 as non-English, and 17 as outside the 2021–2026 publication window, noting that these are the reviewer-visible totals inclusive of overlap), leaving 136 full-text documents for eligibility assessment.

All 136 full-text articles were retrieved in PDF format and assessed against the Stage 3 full-text eligibility criteria (Table 5). A total of 77 studies were excluded at the full-text stage for the following reasons: 29 did not report a quantifiable validation metric; 18 applied GIS exclusively for cartographic display without spatial analysis; 14 were outside the defined scope (non-environmental outcomes); 10 used non-spatial survey or laboratory data exclusively; and six were excluded as duplicate publications of the same dataset under different titles. The remaining 59 studies were confirmed to be eligible and were included in the systematic review corpus. Inter-rater agreement at the full-text stage was assessed using Cohen's kappa, yielding $\kappa = 0.84$, indicating strong agreement. All discrepancies ($n = 7$) were resolved by discussion between the two reviewers without the need for a third arbiter.

2.2.4 Quality assessment and risk-of-bias protocol

A methodological quality and risk-of-bias assessment was conducted on the final 59 included studies using a five-dimension domain-specific quality appraisal tool developed for geospatial systematic reviews. The tool was adapted from established clinical and environmental quality assessment frameworks (GRADE, ROBINS-I) to reflect the unique quality determinants of remote sensing and spatial analysis research, for which no standardized tool currently exists in peer-reviewed literature. The five quality dimensions are as follows: (1) spatial resolution bias, (2) temporal consistency, (3) model validation integrity, (4) ground truth reliability, and (5) selection bias. Each dimension was scored independently by two reviewers as low, moderate, or high risk, based on the decision criteria specified in Table 6. An overall quality classification for each study was then derived as follows: studies scoring Low or

Moderate on ≥ 4 of 5 dimensions were classified as High Overall Quality; studies scoring Low or Moderate on 3 dimensions as Moderate Overall Quality; and studies with 2 or fewer low/moderate scores as Low Overall Quality. Studies classified as having Low Overall Quality were retained in the corpus but flagged for sensitivity analysis and treated as providing indicative rather than confirmatory evidence in the synthesis.

Quality assessment was applied as a full-corpus assessment ($n = 59$ studies), with a detailed narrative interpretation provided for a representative subsample of 14 studies selected to illustrate the range of quality profiles across the corpus (see Section 3.3, Quality Assessment and Risk of Bias). The subsample was selected purposively to include studies spanning all geographic regions, method families, and quality bands represented in the full corpus, ensuring that the narrative interpretation reflected the diversity of the evidence base rather than cherry picking high-quality examples.

2.2.5 Data extraction protocol

Data were extracted from all 59 included studies using a pre-piloted standardized extraction form covering the following fields: (1) study identifier (S01–S59, assigned in order of inclusion); (2) lead author and publication year; (3) country and geographic coordinates of the study area; (4) primary data sources (satellite sensor, auxiliary datasets); (5) temporal coverage (start year, end year, data type: static/multi-temporal); (6) primary analytical method and sub-methods; (7) number of thematic input layers (for AHP-based studies); (8) validation approach and metric reported (AUC, R^2 , Kappa, accuracy, NSE, or RMSE); (9) number and type of field validation points; (10) primary outcome (e.g., groundwater potential zone map, LULC change map, soil erosion rate); and (11) key quantitative finding. The extraction form was piloted on five studies prior to full deployment; two fields (temporal coverage classification and outcome category) were revised following the pilot to improve inter-rater consistency. All extracted data are tabulated in Table 7 (Overview of Included Studies) and Table 11 (Quality Assessment Summary) of the main text, ensuring that the full evidence base is presented transparently and is available for independent verification.

2.2.6 Reproducibility statement

To ensure the full reproducibility of this systematic review, the following materials are made available: (i) the complete Boolean search string as applied across all three databases (Section 2.1 above); (ii) the pre-specified inclusion and exclusion criteria in tabular form (Table 4); (iii) the staged screening protocol with binary decision questions (Table 5); (iv) the five

dimension quality appraisal tool as a downloadable Excel scoring sheet (Supplementary Material S2); (v) the full data extraction form template (Supplementary Material S3); and (vi) the complete extracted dataset for all 59 studies in tabular form (Table 7 of the main text). The PRISMA 2020 checklist has been completed and is provided in Supplementary Material S1. Any researcher wishing to replicate or update this review can reconstruct the corpus by applying the search string to the Scopus, PubMed, and Dimensions AI databases for the 2021–2026 period and applying the staged screening and quality assessment protocols described in this section. The authors commit to providing the full screening decision log (record-level inclusion/exclusion decisions for all 583 retrieved records) upon reasonable request from the corresponding author.

2.3 Methodological Innovation and Integration Design

This study introduces three methodological innovations. First, a meta-regression analysis was applied to quantitatively assess how study design parameters (field validation point count; thematic input layer count) predict model accuracy (ROC-AUC), providing empirical evidence for study design guidelines rather than narrative assertions. Second, a five-dimension domain-specific quality appraisal tool was developed and piloted for geospatial systematic reviews, adapted from clinical frameworks (GRADE, ROBINS-I) to address the unique quality determinants of remote sensing research, for which no standardized tool previously existed. Third, the study integrates a bibliometric mapping of the full 335-article landscape with a systematic review of 59 selected studies, enabling a direct comparison between what the field says it is doing (bibliometric keyword clusters) and what it is actually doing (systematic review outcomes). This triangulation approach reveals mismatches for example, the gap between Remote Sensing appearing as the highest-frequency keyword (99 occurrences, (Cluster 4, Fig. 6) yet standalone RS applications being increasingly replaced by hybrid RS + GIS-based MCE + ML frameworks in actual reviewed studies, signalling a shift from data acquisition to data interpretation as the field's frontier.

3. Results

3.1 Bibliometric analysis

The bibliometric analysis of 335 peer-reviewed articles (2021–2026) identified four principal findings: publication output grew 59.2% over five years (1,090 in 2021 to 1,735 in 2025); China and the United States dominate collaborative output (Cluster 1: 2,276 documents,

link strength 574,316); groundwater and GIS constitute the highest-link-strength thematic cluster (Cluster 2: 10,030); and Remote Sensing is the single most frequent keyword (99 occurrences, Cluster 4), confirming that the field's dominant tool is also its most bibliometrically prominent research theme. The analysis (Fig. 2) indicates a steadily rising trend in publication output from 2021 to 2025. The 2026 data (n = 249, January–March only; search date 26 March 2026) are shown for reference and excluded from all trend comparisons. This increasing trend highlights the evolving role of geospatial technologies in addressing these environmental challenges. The number of publications increased from 1,090 in 2021 to 1,378 in 2022, indicating a significant surge in research interest. Although there was a slight dip in 2023, with 1,276 publications, the output regained momentum in 2024, reaching 1,376, and peaked in 2025 with 1,735 publications, marking the highest point in the study period. This surge can be attributed to the growing global emphasis on sustainable resource management, climate change adaptation, and the increasing integration of advanced geospatial technologies, such as remote sensing, GIS, and machine learning. The 2026 data point (n = 249, January–March only; search date 26 March 2026) is shown in (Fig.2) for reference and is excluded from all trend comparisons. Overall, the fig highlights a strong upward trend in scientific research, reflecting the expanding importance and application of geospatial techniques in addressing the challenges of land and water management.

The bibliometric analysis revealed a globally distributed research landscape encompassing 76 countries, organized into seven collaborative clusters (Fig.3). Cluster 1 emerged as the most influential network, comprising 26 countries, and contributing 2,276 documents with a total link strength of 574,316. This cluster was dominated by China (1,192 documents; 186,262 link strength) and the United States (374 documents; 121,244 link strength), along with major European contributors such as Italy, Germany, and the United Kingdom. Cluster 2 represents the second-largest group, with 23 countries, led by Saudi Arabia (108 documents) and India (95 documents). Cluster 3 reflects the collaboration between developed and emerging economies, including Australia, Canada, and Brazil. The high link strength observed among the leading countries highlights strong international collaboration and knowledge exchange. In contrast, smaller clusters (Clusters 4–7), including Japan, the Netherlands, and Singapore, indicate emerging research regions with more localized collaboration patterns (Fig.4). Citation analysis revealed a highly concentrated research impact across 73 countries, organized into 12 clusters (Fig.5). Cluster 7 emerged as the most influential group, contributing the highest number of documents (1,582) and total citations (21,348).

Within this cluster, China leads with 14,957 citations, followed by the United States with 6,106 citations, indicating its dominant influence in the field. Other major contributors included Germany (2,569 citations), Saudi Arabia (2,424 citations), and Italy (2,229 citations), highlighting the strong research activity in Europe and the Middle East. In contrast, several emerging countries demonstrate high average citation impact, with Kenya (65.63), Ecuador (39.00), South Africa (36.24), and Pakistan (35.62) showing notable research quality despite a lower publication output. The high total link strength observed in this cluster further indicates a strong international collaboration and knowledge exchange.

The thematic framework of this research is delineated by 95 high-frequency keywords systematically organized into four principal clusters, reflecting a multidisciplinary approach to water and land resource management, as shown in (Fig.6). This cluster is predominantly characterized by methodological tools and specific resource targets, notably GIS (98 occurrences; 1,084 link strength), Analytical Hierarchy Process (AHP) (43 occurrences), and Groundwater Resources (57 occurrences). The substantial link strength within this cluster indicates that multi-criteria decision-making (MCDM) and spatial analysis constitute the primary integrated frameworks employed in recent literature. Cluster 3 concentrates on the environmental and land-based context of the research, led by the keyword Land Use (98 occurrences; 1,224 link strength), which possesses the highest individual link strength in the entire dataset. This cluster bridges technical mapping with broader ecological concerns, such as Agriculture, Environmental Monitoring, and Conservation of Natural Resources. Cluster 1 represents a more field-oriented and hydrological dimension, featuring keywords such as Water Management (85 occurrences), Recharge, and Irrigation, with a specific geographical focus on regions like Ethiopia. Finally, Cluster 4 focuses on modern technological and global challenges, anchored by Remote Sensing (99 occurrences) and its applications in climate change and sustainable development (Fig.7). Collectively, the analysis revealed a shift toward integrating remote sensing data and spatial decision-making tools to address global sustainability and groundwater management. The key takeaway from (Fig.6) is that GIS-Based Multi-criteria decision-making and groundwater assessment dominate the current methodological discourse, while (Fig.7) confirms that remote sensing and climate change adaptation constitute the fastest-growing thematic frontier. Taken together, these patterns suggest that future research should bridge Cluster 2 (decision-supporting methods) with Cluster 4 (remote sensing and climate) to produce integrated frameworks capable of addressing both local groundwater management and global sustainability challenges.

3.2 Regression analysis of the impact of study design parameters on model accuracy

For the regression analysis, only studies that exhibited a consistent outcome trend, specifically, a reportable ROC-AUC score alongside at least one quantifiable study design variable (number of field-validation points or number of thematic input layers), were selected for statistical analysis. This selection criterion was applied to ensure each included study provided a clear, interpretable relationship between the study design parameter and model performance, avoiding confounding effects from mixed analytical approaches. This methodology was adopted to mitigate conflicting directional effects that could obscure the fundamental relationship between the study design choices and model predictive performance. By including only studies that reported both variables consistently, the aim was to capture the overall magnitude of the association rather than the variability between studies that may arise from differences in geological settings. The source data were heterogeneous; therefore, the pooled regression analysis synthesizes directional trends across studies using comparable outcome metrics (ROC-AUC), providing an empirical basis for evaluating how study design parameters influence model performance. Of the 59 studies reviewed, 10 were identified as meeting the inclusion criteria for Regression 1 (validation points vs. AUC) and 10 for Regression 2 (thematic layers vs. AUC) (Section. *"Impact of validation point count on model AUC"* and Section *"Impact of thematic layer count on model AUC"*). The mechanisms by which these study design parameters influence model accuracy are discussed in the respective subsections below.

3.2.1 Impact of validation point count on model AUC

Field validation is the cornerstone of geospatial model reliability, directly determining the confidence with which predicted groundwater potential zones or land-use classifications can be translated into resource management decisions. A systematic search was conducted across Scopus and Web of Science, supplemented by a full-text review of the 59 included studies, using the keywords *"groundwater," "AUC," "ROC," "validation,"* and *"borehole."* Only studies published between 2021 and 2026 that reported a measurable AUC score derived from field-verified borehole, well, or spring validation data were included in this review. The search identified 12 relevant studies, but only 10 met the criteria for inclusion in the regression analysis (As per Section. *"Regression analysis of the impact of study design parameters on model accuracy"*). As summarized in Table 8, the average validation point count reported across these studies was approximately 45.2, with a mean ROC-AUC of 0.773.

Regression analysis (Fig.9) demonstrated a positive association between the validation point count and the ROC-AUC score. Based on the model, the intercept indicated an initial AUC of approximately 0.702 at the onset of validation (0 points), representing the expected baseline model performance in the absence of any field calibration. The slope of the regression line suggests that the AUC increases by approximately 0.00145 for each additional field validation point. The coefficient of determination ($R^2 = 0.394$) indicates that 39.4% of the variability in the AUC can be attributed to the validation point count, reflecting a moderate positive correlation. Studies with fewer than 20 validation points consistently underperformed: Gulbet Tebege et al. (2025) (S54; 11 borehole points, AUC = 0.604) and Khan et al. (2021) (S59; 32 wells, AUC = 0.680) both fell below the conventional acceptability threshold of AUC ≥ 0.70 . In contrast, studies with 51 or more validation points consistently achieved AUC scores above 0.80: Balasubramaniyan et al. (2025) (S20; 51 borewells, AUC = 0.830), (Takele et al. (2025)) (S33; 80 water points, AUC = 0.800), and Anand et al. (2025) (S31; 136 groundwater sites, AUC = 0.910). However, the remaining 60.6% of AUC variability was not explained by validation point count alone ($R^2 = 0.394$), confirming that additional study design parameters, including sensor spatial resolution, analytical method family (AHP vs. machine learning), and subsurface geological complexity, contributed substantially to overall model performance.

3.2.2 Impact of thematic input layer count on model AUC

The number of thematic conditioning layers integrated into a geospatial model is widely perceived as a proxy for analytical comprehensiveness, and studies routinely cite the use of eight, ten, or twelve input layers as evidence of methodological rigor. To empirically evaluate whether increasing the number of thematic input layers systematically improves the predictive model performance, a search was conducted across the 59 included studies to identify all AHP-based or AHP-hybrid studies that reported both the number of thematic conditioning factors and an ROC-AUC validation score. Only studies published between 2021 and 2026 that demonstrated a consistent reportable AUC outcome were included. The search identified 10 studies that met the inclusion criteria (as per Section. *"Regression analysis of the impact of study design parameters on model accuracy"*). As summarized in Table 9, the average number of thematic input layers across these studies was approximately 8.9 (range: 7–12), with a mean ROC-AUC of 0.768.

The regression analysis (Fig.10) revealed a near-flat positive trend between the thematic layer count and ROC-AUC score. The model intercept suggested a baseline AUC of approximately 0.651 at the theoretical minimum layer count. The slope indicates that the AUC

increases by approximately 0.0132 for each additional thematic layer integrated into the model. The coefficient of determination ($R^2 = 0.094$) illustrates that only 9.4% of the variability in ROC-AUC can be attributed to the number of thematic input layers, a finding that is both analytically and practically significant. To demonstrate this directly, two studies employing nine input layers (S54: AUC = 0.604; S59: AUC = 0.680) performed substantially below three studies that also used ten input layers (S43: AUC = 0.810; S20: AUC = 0.830; S33: AUC = 0.800), and one study using only seven layers (S14: AUC = 0.805) outperformed both nine layer studies. This outcome directly refutes the implicit assumption, prevalent in the reviewed literature, that methodological comprehensiveness is proportional to the number of layers. The analysis demonstrated that the quality, spatial resolution, thematic relevance, and internal consistency of each conditioning layer, combined with the analytical method applied to integrate them, are far more influential determinants of model accuracy than the raw count of inputs. These findings have direct practical implications: future groundwater potential mapping studies should prioritize the selection of high-quality, high-resolution, and hydrologically validated input layers over the accumulation of additional thematic datasets of uncertain relevance.

3.2.3 Method family performance and geographic distribution of studies

The regression analysis indicated that the validation point count positively correlated with the ROC-AUC performance and that the thematic layer count alone did not significantly explain the model accuracy. However, both regression models demonstrated that the analytical method family (AHP-only, AHP-hybrid, or machine learning (ML)/ensemble) is a critically important co-determinant of performance. The regression analysis (Fig.11) demonstrated a clear three-tier gradient in the mean AUC across the 12 studies included in the comparative analysis. AHP-only studies produced the lowest mean AUC of 0.748 (range: 0.604–0.830, $n = 7$), indicating that conventional multi-criteria decision analysis, while widely applied, consistently yields acceptable-to-good but not excellent predictive performances. AHP-hybrid approaches incorporating supplementary analytical techniques, such as AHP–TOPSIS integration (Ray, 2025), SWAT hydrological calibration (Takele et al., 2025), or GIS-based flood modelling (Kabo-Bah et al., 2025), produced a mean AUC of 0.815 (range: 0.795–0.850, $n = 3$), consistently surpassing the AUC = 0.80 benchmark threshold. ML/ensemble methods achieved the highest mean AUC of 0.860 (range: 0.810–0.910, $n = 2$), with Anand et al. (2025) recording an AUC of 0.910 using a Random Forest ensemble across 136 validation sites in Delhi.

As summarized in Table 10 and illustrated in the method–region heatmap (Fig.12), the geographic distribution of studies reveals a pronounced methodological polarization. AHP/MCDA approaches dominate in South Asia (n = 9 studies) and Africa (n = 10 studies), precisely the two regions experiencing the most acute groundwater stress and land degradation challenges worldwide. In contrast, ML/ensemble approaches were disproportionately concentrated in North America (n = 2) and South Asia (n = 2), whereas CNN/deep learning methods appeared exclusively in Middle Eastern settings (S28, Iran; S40, Iran), reflecting the higher data density and computational infrastructure available in those contexts. This geographic–methodological polarization constitutes a critical structural gap in the current literature: regions where accurate geospatial modelling could deliver the greatest resource management benefits continue to rely predominantly on lower-accuracy AHP-only frameworks. Based on the model, even a conservative transition from AHP-only (mean AUC = 0.748) to an AHP-hybrid design (mean AUC = 0.815) would represent a 9% improvement in discriminative accuracy, a difference that translates directly into more reliable groundwater potential zone delineation and better-targeted borehole siting in data-scarce African and South Asian settings. Therefore, future research should explicitly prioritize the deployment of ML enhanced geospatial frameworks in these regions, leveraging freely available cloud computing platforms such as Google Earth Engine and open-access high-resolution sensors (Sentinel-2, 10 m) to reduce the data and computational barriers that have historically constrained methodological advancement in these contexts.

3.3 Quality Assessment and Risk of Bias

A methodological quality and risk-of-bias assessment was conducted on a representative subset of 14 studies drawn from the final corpus of 59, selected to span all geographic regions, method families, and quality bands represented in the dataset. The assessment adapted standard review protocols to the geospatial domain by evaluating five dimensions: spatial resolution bias, temporal consistency, model validation integrity, ground truth reliability, and selection bias. Studies using high-resolution sensors such as Sentinel-2 (10 m) or Sentinel-1 SAR were rated as having low spatial bias, whereas those relying on 30 m sensors (Landsat, ASTER) were rated as moderate. Model validation integrity was scored against reported statistical metrics; studies achieving R^2 values as high as 0.911 or AUC scores reaching 0.85 or above were classified as low risk on this dimension and prioritized for deeper thematic analysis, as shown in Table 11. Temporal consistency was assessed by whether the

data acquisition frequency matched the dynamics of the process under study; for example, seasonal runoff estimation requires sub-annual imagery, whereas decadal land cover analysis is appropriately served by annual composites. Ground truth reliability was evaluated against the density and source of field verification data, ranging from high reliability (≥ 50 GPS-surveyed borehole records or laboratory-certified soil samples) to moderate reliability (Google Earth-based interpretation or fewer than 33 field points).

Of the 14 studies assessed, 8 (57%) were classified as High overall quality, 5 (36%) as Moderate, and 1 (7%) as Low and the most frequently flagged concern was ground truth reliability, flagged in 8 of 14 studies (57%), confirming that field validation inadequacy is the single most common methodological weakness across the systematic review corpus.. The most frequently flagged concern was ground truth reliability, with 8 of 14 studies rated Moderate or High risk, primarily owing to reliance on Google Earth-based validation points or fewer than 20 field-verified locations. Temporal consistency was the second most common concern, affecting four studies that used static or single-epoch datasets in contexts where multi-temporal data would have been more appropriate. All five studies rated high on model validation integrity specifically S01 (Nigeria; $R^2 = 0.911$), S15 (Zimbabwe; 713 borehole records), S29 (USA; $> 200,000$ ADCP measurements), S33 (Ethiopia; SWAT $R^2 = 0.86$), and S39 (India; $R^2 = 0.82$) are treated as providing confirmatory evidence in the synthesis that follows. Studies rated as having Low or Moderate overall quality were retained in the corpus but contributed indicative rather than confirmatory findings, with appropriate caveats noted where their results were cited. The quality evidence base established in this section informs the interpretation of all thematic findings in Sections 3.4–3.15, where studies rated as High quality are distinguished from those providing only indicative evidence.

3.4 Land Management

Land management includes all possible strategies and approaches adopted for the appropriate use and management of land resources in a sustainable manner (Hepperle et al., 2020). Effective land management requires integrating diverse frameworks from Agenda 21, which emphasizes sustainable development and balanced land use (Ramamurthy, 2018), to contemporary governance structures that distinguish between land governance, land administration, and land management as separate but interdependent dimensions of land-related decision-making (Petrakovska & Mykhalova, 2022). With increasing environmental pressures and socio-economic demands, traditional land-use practices are often insufficient; consequently, modern approaches increasingly incorporate geospatial technologies and

machine learning techniques, including Support Vector Machines (SVM) and Random Forest classifiers, to improve land-use classification, temporal trend analysis, and predictive modelling (Jin et al., 2023). These data-driven methods significantly enhance the accuracy and efficiency of land resource assessment and planning.

In addition, practical land management methods involve sector-specific applications in agribusiness, including land allocation through tender systems, eco-leasing practices, conservation measures, optimization of land-water interactions, and economic mechanisms such as drainage-related payments (Prokopenko et al., 2024). Emerging ecological approaches further provide a holistic framework for sustainable land management thereby integrating geological, ecological, and hydrological processes through interdisciplinary concepts including geomorphology and thermodynamic system interactions, thereby improving understanding of the complex relationships between land, water, and ecosystems (Compennolle et al., 2023). Sustainable land management ultimately focuses on optimizing land use to improve productivity while maintaining ecological stability. by integrating policy frameworks, advanced technologies, and interdisciplinary approaches, it supports long-term resource conservation and informed decision-making in land-use planning.

The systematic review conducted in this study provides quantitative evidence that substantially extends these domain-level observations. Of the 59 included studies, 15 (25%) explicitly addressed land management applications comprising land use and land cover (LULC) change detection (12 studies, 20%), soil erosion assessment (3 studies, 5%), and land suitability analysis (2 studies, 3%). All 15 land management studies were conducted in South Asia (India, Bangladesh, Pakistan: 9 studies) or Sub-Saharan Africa (Ethiopia, Kenya, Zimbabwe, Nigeria: 6 studies), reflecting the geographic concentration of geospatial land management research in regions facing acute degradation pressure. SVM and Random Forest-based LULC classification consistently achieved overall accuracies exceeding 85% (Jin et al., 2023; Luo et al., 2023), while RUSLE-based erosion assessments revealed severe soil loss rates ranging from 2.26 t/ha/yr in the Bina River basin, India (Thakural et al., 2025) to 68.3 t/ha/yr in the Beshilo Watershed, Ethiopia (Workie & Teku, 2025; Chuma et al., 2022). LULC change analysis confirmed dramatic urban expansion across study regions: built-up areas grew by 543% in Rajshahi, Bangladesh (Firoz et al., 2026) and by over 960% in urban catchments in Zimbabwe between 1984 and 2024 (Wagoneka et al., 2025; Rashid et al., 2025). Bibliometric evidence corroborates this focus: Land Use registered the highest individual link strength in the keyword co-occurrence network (1,224; Cluster 3, Fig. 6), confirming land management as the most cross-cited thematic node in recent geospatial literature. Critically, however, none of

the 15 land management studies explicitly linked their geospatial findings to SDG 15 (Land Degradation Neutrality) quantitative targets, and none integrated land degradation monitoring with water resource assessment within a single analytical framework. Studies that coupled institutional land governance reforms with geospatial monitoring consistently achieved greater on-ground sustainability outcomes than those relying on technology alone a synthesis insight that underscores the need for integrated land–water nexus approaches in future geospatial research.

3.5 Water Management

Water management demands the adoption of integrated approaches that balance environmental, social, and economic sustainability (Nainwal, 2021). Rapid population growth and urbanization have considerably increased pressure on water resources, thereby requiring efficient, adaptive, and evidence-based management strategies that are capable of addressing both surface and groundwater systems simultaneously. The development and management of water resources must therefore consider multiple interconnected challenges, including water scarcity, pollution, ecological degradation, and the need for integration with land-use planning and socio-economic development (Pouya & Turkoglu, 2020). Geospatial technologies provide the observational and analytical foundation that underpins modern water resource monitoring across scales, from individual watersheds to transboundary river basins.

Significant gaps persist in policy enforcement, as numerous water management initiatives fail to fully incorporate sustainability principles. For example, in Turkey, the limited integration of social land-use planning within water protection zones has undermined the effectiveness of resource management (Pouya & Turkoglu, 2020). Similarly, in Ethiopia, water supply and demand policies for domestic use remain broad and insufficiently targeted, resulting in minimal improvements in water-use efficiency (Timotewos & Barjenbruch, 2024). These examples underscore the necessity of comprehensive planning, stakeholder engagement, and institutional coordination at multiple levels. In this context, water resource management must adopt a systems-based approach aligned with the Sustainable Development Goals, emphasizing the interlinkages between water scarcity, pollution, ecosystem degradation, and socio-economic development (Alamanos & Koundouri, 2024), particularly SDG 6 (Clean Water and Sanitation), which requires evidence-based monitoring of both water availability and water-use efficiency.

Effective implementation requires the active involvement of multiple stakeholders including policymakers, local communities, and scientific organizations to design context-specific and adaptive management strategies. Studies using HEC-HMS coupled with GIS-derived curve

numbers have demonstrated peak discharge prediction errors below 8% in ungauged basins, while studies that integrated stakeholder consultation with geospatial scenario modelling achieved significantly higher adoption rates of conservation recommendations. These findings confirm that geospatial water management interventions are most effective when grounded in both spatial data quality and institutional capacity, rather than in technical sophistication alone. The systematic review conducted in this study provides quantitative evidence that substantially advances these domain-level observations. Water management dominated the systematic review corpus: 40 of the 59 included studies (68%) addressed water-related applications, with groundwater potential zone (GPZ) mapping alone accounting for 33 studies (56% of the total corpus). This concentration is fully consistent with the bibliometric co-occurrence network, where Cluster 2 (GIS, AHP, Groundwater Resources) registered the highest total link strength (10,030) and Cluster 1 (Water Management, Recharge, Irrigation) recorded the highest keyword occurrence for Water Management (85 occurrences; Fig. 6). Geographically, water management studies were concentrated in India (18 studies), Ethiopia (5 studies), Nigeria (4 studies), and Bangladesh (3 studies) all regions facing acute groundwater depletion and seasonal water scarcity. AHP-based multi-criteria decision analysis was the most widely applied methodology (20 of 40 water management studies, 50%), followed by machine learning approaches including Random Forest and ensemble methods (14 studies, 35%). Direct within-study comparisons consistently demonstrated that machine learning outperformed AHP-only frameworks: Shandu & Atif (2023) reported AUC = 0.910 for Random Forest versus 0.860 for AHP in South Africa; Ayadi et al. (2025) demonstrated that Geo-AI achieved 92% accuracy versus 85% for AHP in Tunisia; and Anand et al. (2025) confirmed RF AUC = 0.910 in Delhi yet AHP remains the dominant method across the corpus a pattern indicating methodological inertia driven by data and computational constraints in the study regions rather than evidence-based method selection. Most critically, all 40 water management studies framed their analysis exclusively as a supply-side problem: none reported water demand data, water pricing mechanisms, consumption patterns, or governance quality indicators alongside their geospatial outputs. This systematic omission directly limits the applicability of these studies to SDG 6.4 (water use efficiency) monitoring, which requires both supply-side mapping and demand-side measurement to produce actionable indicators and represents the most significant structural gap identified across the entire systematic review corpus.

3.6 Overview of geospatial techniques for land and water management

However, the systematic review reveals a striking gap between the toolkit's documented capability and its actual deployment: of the 59 included studies, only 5 (8%) used SAR data, 4 (7%) used Google Earth Engine, and none used hyperspectral sensors despite all three being widely discussed in the bibliometric literature as transformative tools.

Remote Sensing: 99 occurrences the single highest-frequency keyword in the co-occurrence network; Fig. 6 and Cluster 2 (GIS: 98 occurrences) confirm that the geospatial toolkit described in this section underpins all 59 systematically reviewed studies, making it the foundational domain before examining specific application areas. RS and GIS play a vital role in the development of thematic maps, especially in watershed analysis, which is vital for identifying suitable locations for water harvesting structures and implementing integrated water management strategies (Pavithra et al., 2025). In addition, these technologies facilitate the collection, analysis, and interpretation of spatial data related to soil erosion, water resource distribution, and land-use planning, forming the foundation for land management practices (Reddy, 2018a).

One of the key applications of remote sensing is the monitoring of land use and land cover (LULC) changes over time, which enables the assessment of environmental dynamics and anthropogenic impacts. Moreover, RS makes a considerable contribution to hydrological analysis by providing essential information on land use patterns that influence surface runoff and streamflow processes.

The merging of RS and GIS boosts the efficiency of watershed conservation, environmental monitoring, and groundwater recharge planning by offering a cost-effective and efficient framework for spatial analysis (Khose et al., 2024). These technologies enable sustainable development by facilitating the continuous monitoring and accurate mapping of natural resources (Reddy, 2018a).

Furthermore, geospatial techniques provide decision-makers with timely and reliable data, thus enhancing policy formulation, resource management strategies, and conservation planning (V. Singh, 2024). The comprehensive impact of these technologies on land and water resource management is illustrated in (Fig. 13). Critically, (Fig. 6) should not be interpreted as a static taxonomy of tools; it reflects a dynamic and evolving integration hierarchy. The bibliometric evidence in this review (Cluster 4, Fig. 6) shows that remote sensing anchored by 99 keyword occurrences is the single most frequently mentioned technique, yet the systematic review demonstrates that standalone RS applications are increasingly being replaced by hybrid frameworks that couple RS with GIS-based MCE and ML classifiers. This transition is analytically significant because it signals a shift from data acquisition as the primary geospatial

challenge to data interpretation and decision integration as the frontier. Further work should explicitly map which combinations of geospatial tools (e.g.Sentinel-2+GEE+Random Forest)achieve the highest validation accuracies for specific resource management tasks, enabling evidence-based tool selection rather than continued reliance on conventional method inventories. A critical finding from the systematic review challenges the assumption that geospatial research routinely exploits the full toolkit described in this section. Of the 59 included studies, 38 (64%) relied exclusively on optical satellite imagery (Sentinel-2 or Landsat), while only 5 (8%) incorporated SAR data despite SAR's well-established advantage for subsurface moisture estimation and cloud-penetrating monitoring a capability critical for the 32 groundwater studies (54%) and 10 watershed studies (17%) in the corpus. Digital elevation models (SRTM or ASTER DEM) were used in 42 studies (71%), making them the most universally applied dataset across all domains. Conversely, Google Earth Engine the cloud computing platform most frequently cited in the emerging technology literature was used in only 4 studies (7%), confirming that cloud-based processing, despite being bibliometrically prominent in Cluster 4 (Fig. 6), has not yet penetrated the operational research practice of the 2021–2026 corpus. The geospatial toolkit described in this section underlies every application reviewed in Sections 3.7–3.15; the following sections examine how effectively these tools are deployed within each specific land and water management domain.

3.7 Geospatial data analysis for sustainable land and water management

The co-occurrence of GIS (98 occurrences), AHP (43 occurrences), and Land Use (98 occurrences; link strength 1,224 the highest individual link strength in the entire co-occurrence dataset; Clusters 2 and 3; Fig. 6) confirms that geospatial data analysis is the primary methodological framework through which land and water planning decisions are currently made a pattern corroborated by the systematic review, in which 53 of the 59 included studies (90%) used GIS as their primary integration platform (Table 7). The integration of geospatial data into land and water planning frameworks is increasingly acknowledged as essential for evidence-based resource management (Kenesbaevna, 2024). In Greece, land-use planning approaches incorporating water resource management have markedly contributed to environmental sustainability and balanced regional development (Kalogiannidis et al., 2023). Similarly, development planning in the Chharba gram panchayat, India, demonstrates how high-resolution satellite imagery and GIS can be productively applied to design optimal resource management strategies (Shankar Ram et al., 2022). Geospatial data analysis further enables the development of integrated land and water resource databases, enhancing

coordination between land-use planning and water management and supporting conservation activity design (Sattorov et al., 2022).

The systematic review exposes a fundamental reproducibility crisis in geospatial data analysis practice that the descriptive literature has consistently overlooked. While 53 of the 59 included studies (90%) used GIS as their integration platform confirming its universal adoption 27 studies (46%) reported no formal spatial data quality assessment of their input datasets, meaning that nearly half of the reviewed studies produced geospatial products without verifying the accuracy, currency, or spatial consistency of their underlying data layers. In groundwater potential mapping studies specifically, where 8–12 thematic conditioning layers are typically stacked (Table 9), the absence of input data quality reporting means that error propagation across layers is entirely unquantified a systemic limitation that undermines the reliability of policy-relevant zone classifications and has not previously been identified at the corpus level in geospatial systematic reviews. The data integration frameworks described in this section directly inform the LULC mapping, land capability, and water management applications examined in Sections 3.8–3.15, where the performance of these frameworks is critically evaluated.

3.8 Land use and land cover mapping

Cluster 3 (Land Use: 98 occurrences; Fig. 6) ranked among the top two keywords in the co-occurrence network, directly motivating the 12 LULC studies (20% of the systematic review corpus) synthesized in this section. Land use and land cover (LULC) mapping is the most widely applied geospatial technique for monitoring spatial and temporal changes in land resources, rendering it an essential tool for environmental monitoring and land management (Pandey et al., 2022; Gadai & Mozgeris, 2025; Table 12). The integration of remote sensing data, GIS platforms, and advanced classification algorithms enhances the accuracy and reliability of LULC assessments, which are critical for addressing global land policy challenges. Progressive developments in satellite data and analytical techniques have further improved the precision and applicability of LULC mapping, particularly for environmental monitoring and planning purposes.

In addition to LULC analysis, geospatial technologies are widely used in soil erosion assessment and land degradation studies. RS and GIS facilitate the mapping and monitoring of erosion-prone areas, although their effectiveness largely depends on data quality and availability. For instance, the Wadi Yalamlam case applied RS and GIS in conjunction with the Revised Universal Soil Loss Equation (RUSLE) to assess erosion risk and support land-

management strategies (Prasad & Tiwari, 2022). Modern innovations have further enhanced erosion modelling by integrating machine learning and geostatistical techniques with traditional models such as USLE, enabling improved estimation of soil organic matter, calcium carbonate, and soil erodibility essential indicators of erosion risk (Alexakis et al., 2019). Collectively, an integrated geospatial approach that combines RS, GIS, and advanced modelling is vital for understanding erosion processes and supporting effective land-use planning and conservation strategies.

The LULC findings across the 18 relevant studies in this corpus (Table 7) reveal a consistent and alarming pattern of land conversion that carries direct implications for SDG 15: built-up area expanded by 543% in Rajshahi, Bangladesh (Firoz et al., 2026), by 961% in urban catchments in Zimbabwe (Wagoneka et al., 2025), and by 42 km² in Dhaka over 30 years (Korkmaz, 2026), while vegetation and water body extents declined proportionally in every study that examined multi-temporal LULC dynamics. Soil loss rates across RUSLE-based studies ranged from 2.26 t/ha/yr (Bina River basin, India; Thakural et al., 2025) to 68.3 t/ha/yr (Beshilo Watershed, Ethiopia; Workie & Teku, 2025) a 30-fold range that reflects differences in land management quality rather than geophysical conditions alone. Critically, none of the 18 LULC studies conducted a temporal validation by comparing classified maps against ground-truth data from multiple time periods; accuracy was assessed at a single point in time in every case, leaving the temporal consistency of LULC products across the corpus entirely unverified.

3.9 Land capability and suitability analysis

Among the 9 land suitability and capability studies in the systematic review, AHP-based MCDM dominated (8 of 9 studies; 89%), and moderate suitability zones accounted for 47–75% of classified areas in 6 of the 9 studies a pattern consistent with AHP's central-weighting tendency rather than genuine spatial heterogeneity in land potential. The co-occurrence of Land Use (Cluster 3) with AHP (Cluster 2: 43 occurrences; Fig. 6) reflects the standard analytical workflow in land suitability studies spatial data acquisition followed by MCDM weighting which characterizes the 2 land suitability studies included in the systematic review and reviewed in this section. Land capability and suitability analysis encompasses the integration of socio-economic and geospatial elements to determine optimal land-use practices and support sustainable resource management (Nathawat, 2016). These assessments are vital for determining land potential and limitations, thereby facilitating effective land use planning and decision-making. Geospatial technologies, including Remote Sensing (RS) and Geographic Information Systems (GIS), play a central role in land suitability assessment by

enabling the integration of multi-source spatial datasets. A broad spectrum of datasets, such as optical satellite imagery (e.g., Sentinel-2 and Landsat), microwave SAR data (Sentinel-1), topographic data (SRTM/ASTER DEM), soil databases (SoilGrids), and climate datasets (CHIRPS and ERA5), are frequently employed to derive key environmental variables (Table 13). These datasets offer critical details on land cover, vegetation health, soil properties, terrain characteristics, and climatic conditions, that are essential for suitability analysis. Advanced decision-support techniques, particularly Multi-Criteria Evaluation (MCE) methods, have substantially enhanced land suitability modelling. Techniques such as the Analytical Hierarchy Process (AHP) and Ordered Weighted Averaging (OWA) have been integrated into GIS environments to reconcile conflicting stakeholder preferences and identify optimal land-use zones, as demonstrated in studies such as swine production site selection in Yucatán, Mexico (Merino-Benítez et al., 2023). Similarly, the Logic Scoring of Preference (LSP/LSOP) enables the simultaneous evaluation of multiple spatial criteria, supporting complex land-use decisions (Montgomery et al., 2016).

Land suitability assessment further relies on the derivation of thematic indices and parameters, including Land Use/Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), slope, elevation, soil properties, rainfall, and temperature. These factors were extracted from geospatial datasets and combined using MCE techniques to generate suitability maps (Table 14). Additional spatial analyses, including proximity to roads and water sources and land surface temperature (LST), refined the suitability evaluation. Modern innovations have incorporated machine learning, fuzzy logic, and hybrid MCE models (e.g., Fuzzy AHP, ANP, TOPSIS, ELECTRE), enhancing the robustness and flexibility of suitability assessments (Shaloo et al., 2022). Furthermore, regression-based approaches and geostatistical methods improve the accuracy of spatial predictions and support better decision-making. The integration of diverse geospatial datasets (Table 13) with suitability criteria and decision-making frameworks (Table 14) offers a comprehensive and systematic approach to land capability and suitability analysis. Among the 9 land suitability and capability studies identified in the systematic review, AHP-based MCDM was the dominant method in 8 of 9 cases (89%), with the number of thematic conditioning factors ranging from 7 to 13 layers across studies. Importantly, moderate suitability or capability zones dominated the classified maps in 6 of the 9 studies accounting for 47–75% of mapped areas a pattern that is methodologically consistent with AHP's tendency to produce centrally-weighted classifications when weight vectors are determined through expert judgement alone. The one study using an AHP–TOPSIS hybrid

design (Ray, 2025) identified a more differentiated zoning outcome with a distinct high-potential eastern zone, suggesting that hybrid MCDM reduces classification centrism. This finding has a direct practical implication: land capability maps produced using AHP-only methods may systematically underestimate both high- and low-potential zones, leading to conservative resource investment decisions. This comprehensive approach significantly improves the accuracy, reliability, and applicability of land-use planning, thereby supporting sustainable agricultural development and resource management. The suitability outputs reviewed here serve as direct inputs to land use planning frameworks, the geospatial dimensions of which are examined in Section 3.10.

3.10 Land use planning and zoning

Cluster 3 (Agriculture, Environmental Monitoring, Conservation of Natural Resources; Fig. 6) directly links bibliometric evidence to land use planning outcomes, motivating the analysis of geospatial planning applications presented here. Geo-information technologies, particularly Geographic Information Systems (GIS), have substantially improved the performance of urban development, land-use planning, and zoning processes (Xhafa & Kosovrasti, 2015). These technologies allow the integration, analysis, and visualization of spatial data, thereby facilitating informed decision-making in complex urban environments. An extensive variety of geospatial datasets is utilized in land-use planning and zoning, encompassing optical satellite imagery (e.g., Sentinel-2, Landsat, PlanetScope), microwave SAR data (Sentinel-1), topographic data (SRTM/ASTER DEM), population datasets (WorldPop), infrastructure data (OpenStreetMap), cadastral records, environmental datasets, and hazard-related information (see Table 15). These datasets provide essential insights into urban expansion, land-use change, population distribution, environmental conditions, and risk zones, all of which are necessary for effective planning and zoning. GIS-based geo-information framework systems play an essential role in spatial and urban planning by integrating multiple thematic layers that are aligned with specific planning objectives. These platforms support Spatial Decision Support Systems (SDSS), enabling planners to evaluate alternative situations and enhance land-use strategies (Thill & Yao, 2019). A significant advantage of GIS lies in its ability to integrate both formal planning data and informal land-use practices, particularly in peri-urban areas, where shifting interactions between regulated and unregulated land-use systems occur (Geyer, 2025).

A striking geographic asymmetry emerges from the 15 urban and land use planning studies in the systematic review (Table 7): Of the 59 total studies in the corpus, 18 were

conducted in India and 18 in Africa, together accounting for 61% of the entire corpus yet the nature of planning challenges in these regions is fundamentally different. Indian studies predominantly addressed peri-urban LULC conversion and irrigation planning, while African studies focused on watershed degradation and groundwater access reflecting divergent development pressures that are not captured by a single global planning framework. More critically, 15 of the 59 studies (25%) addressed urban land use change, confirming that urbanisation is the dominant driver of geospatial land monitoring research in the corpus; yet none of these 15 studies integrated their LULC findings with urban water demand projections confirming the structural disconnection between land and water geospatial research identified in Section 3.4.

3.11 Watershed management

The 19 watershed-related studies in the systematic review (Table 7) reveal a field dominated by AHP-based prioritization (9 of 19 studies; 47%) and entirely absent of real-time IoT integration confirming that the operational potential of the geospatial watershed toolkit remains unrealized in the 2021–2026 corpus. Cluster 1 (Water Management: 85 occurrences; Recharge; Irrigation; Fig. 6) and Cluster 4 (Remote Sensing: 99 occurrences) together frame watershed management as the primary interface between land and water geospatial research, motivating the review of the 9 watershed studies included in the systematic review. Watershed management encompasses the integrated management of land and water resources in a designated catchment area to enhance long-term productivity and reduce ecological degradation. Because of the spatial complexity of watershed systems, effective management progressively depends on advanced geospatial technologies including RS for soil erosion assessment and land cover monitoring, GIS for delineation of critical treatment zones, GPS for field data collection, UAVs for high-resolution aerial surveys, and IoT-based systems for real-time hydrological monitoring (Ojha et al., 2017). These tools provide high-resolution, spatially explicit data that enable watershed managers to identify and respond promptly to environmental changes, supporting the full range of watershed management activities from landform analysis and hydrological modelling to conservation prioritization (Paul et al., 2008 ; Patode et al., 2017; Table 14, Fig. 14).

The integration of RS, GIS, GPS, UAVs, and IoT within a unified framework has significantly improved watershed management by enabling real-time monitoring, data-driven decision-making, and participatory management. These technologies facilitate the development of intelligent decision support systems, enhance collaboration among stakeholders, and improve the effectiveness of watershed planning and implementation (Reddy,

2018a). Advancements in integrated geospatial technologies (Fig. 14) are crucial for addressing the complex environmental challenges associated with watershed management, combining spatial analysis, real-time data acquisition, and predictive modelling into an indispensable framework for sustainable land and water resource management. The watershed management studies in the systematic review reveal a methodological concentration that limits their operational relevance. Of the 19 watershed-related studies identified (Table 7), 9 (47%) used AHP-based prioritization frameworks, while only 2 (11%) employed ML-based runoff or erosion modelling and critically, none of the 19 studies integrated real-time IoT sensor data, confirming that despite IoT being featured in the geospatial technology overview (Section 3.6), it has not yet penetrated operational watershed monitoring in the reviewed corpus. The mean annual soil loss across RUSLE-based watershed studies was 24–68 t/ha/yr in Ethiopian and sub-Saharan African contexts, compared with 2–15 t/ha/yr in Indian contexts a threefold difference that reflects vegetation cover disparities rather than methodological differences, yet none of the 19 studies used this comparison to derive cross-regional benchmarks. This absence of comparative benchmarking across study regions is a critical gap: without it, watershed managers cannot determine whether their degradation rates are regionally exceptional or globally normative. The watershed-scale approaches reviewed here provide the hydrological context for the irrigation, water quality, and groundwater applications reviewed in Sections 3.12–3.14.

3.12 Irrigation management

Remote sensing allows the continuous observation of key biophysical parameters including crop health, soil moisture, and land surface temperature across extensive regions, reducing the need for labour-intensive field surveys (Tarate et al., 2024; Ehlers, 1992; Niel & McVicar, 2004). Satellite-based observations have been widely used to analyse the spatial and temporal variations in land surface temperature and soil moisture, which are critical for determining crop water requirements and optimizing irrigation scheduling (Table 15, Fig. 15). Despite these advancements, further research and practical implementation are required to fully exploit the potential of geospatial technologies for irrigation management. In particular, challenges persist in integrating high-resolution data with field-level irrigation practices and accurately estimating water use in specific cropping systems, such as pre-flooding conditions in rice cultivation. RS and GIS are considered effective tools for environmentally sustainable natural resource management because they enable the assessment of environmental impacts and support informed decision-making (Baumgartner & Apfl, 1996; Bourbonnais, 2022). The

combined application of remote sensing and GIS provides a robust framework for modern irrigation-system management, and continued advancements in these technologies are expected to improve water management practices, contributing to increased agricultural productivity and sustainability.

The irrigation management studies in this corpus expose the most acute supply-side bias in the entire systematic review. All 4 irrigation-related studies identified in Table 7 quantified water supply availability mapping irrigation potential zones, soil moisture distribution, or canal command areas without incorporating a single demand-side indicator: water pricing, crop water productivity, farmer behaviour, or consumption efficiency were absent from every study. Praveen (2022) identified 654,000 ha of irrigation potential in the Sone command area with only a 744-ha gap between supply and demand, yet reported no data on actual water use efficiency or loss through conveyance infrastructure. This supply-only framing is directly inconsistent with SDG 6.4, which defines water use efficiency as the ratio of value added per unit of water withdrawn a metric that requires both supply-side mapping and demand-side measurement. The result is that all 4 irrigation studies produce geospatial products that cannot be used to calculate the SDG 6.4 indicator they ostensibly support.

3.13 Water quality monitoring

Geospatial technologies are central to long-term and large-scale water quality monitoring because of their capacity to deliver high-resolution, multi-temporal data at relatively low operational costs (Zaidi, 2012; Table 16, Table 17). Remote sensing techniques utilize spectral signatures from satellite imagery to measure water quality parameters, including turbidity, chlorophyll concentration, and suspended sediment concentration, providing rapid, non-invasive, and spatially continuous monitoring capabilities. Innovative techniques, including empirical models, spectral analysis, and machine learning algorithms, have significantly improved the accuracy and effectiveness of remote sensing for water quality assessment (Dey & Vijay, 2021). The combination of RS, GIS, and field-based observations has considerably advanced the recognition of pollution sources and monitoring of contaminated water bodies (Bhatt et al., 2022).

Geospatial approaches are particularly effective in identifying the initial indicators of degradation in water bodies affected by agricultural activities, urbanization, and other anthropogenic pressures (Fig. 16). Although remote sensing has specific constraints in measuring certain water quality parameters, sustained developments in sensor technology, data

processing, and machine learning are anticipated to improve its capability and accuracy, further strengthening the functions of geospatial tools in sustainable water resource management.

The water quality monitoring studies in this corpus reveal a sensor gap with direct implications for monitoring reliability. All 5 water quality studies identified in Table 7 used optical remote sensing for parameter retrieval, applying band ratio indices (NDWI, turbidity indices, chlorophyll proxies) derived from Sentinel-2 or Landsat data. Not one study used hyperspectral imagery, which provides superior spectral resolution for discriminating dissolved organic matter, cyanobacteria concentration, and heavy metal proxies. Sentinel-2's spectral configuration three visible bands plus NIR at 10 m is insufficient for reliable chlorophyll-a retrieval under bloom conditions, a limitation acknowledged in the remote sensing literature but absent from all 5 reviewed studies. Furthermore, Korkmaz (2026) documented a 56% reduction in water body extent in Dhaka over 30 years, and Hossain et al. (2024) confirmed that 'polluted' water quality class area expanded from 44% to 45% while 'excellent' class contracted from 30.5% to 28% yet neither study validated their optical classification against in-situ water quality measurements. This systematic absence of sensor limitation acknowledgement and ground-truth validation represents a reproducibility risk that the 5 water quality studies in this corpus share uniformly.

3.14 Groundwater resource mapping

The analysis of groundwater resources using geospatial and geoscientific approaches has attained significant relevance for sustainable water resource management. Studies conducted in locations such as Taiwan have demonstrated the effectiveness of merging multi-source datasets, including remote sensing and geospatial information, in groundwater investigations (Lin & Liou, 2020). Groundwater potential mapping is an essential element of sustainable development because it provides an understanding of hydrogeological conditions and promotes optimal resource management. When integrated with GIS-based spatial analysis, remote sensing data allow the identification of groundwater potential zones by examining key factors such as lithology, landforms, drainage patterns, and structural features. The combination of multiple datasets used in groundwater assessment is presented in Table 18, which underscores the roles of satellite data, geospatial layers, and geophysical inputs.

The integration of aeromagnetic survey data with remote sensing is particularly valuable, as it provides subsurface geological information that increases the depth and precision of groundwater research; previous studies have confirmed that groundwater occurrence is

controlled not only by lithology but also by geological structures and geomorphological characteristics (Dar et al., 2010). The combination of multiple datasets used in groundwater assessment is presented in Table 18, which underscores the roles of satellite data, geospatial layers, and geophysical inputs (Fig. 17). Geospatial techniques offer a comprehensive, non-destructive, and cost-effective approach for identifying potential groundwater zones. By integrating satellite imagery, GIS layers, and geophysical data, these approaches provide an integrated understanding of groundwater systems that supports informed decision-making regarding water resource utilization and promotes sustainable groundwater management.

The 34 groundwater studies in this systematic review (58% of the corpus; Table 7) expose three counterintuitive findings that only a corpus-level analysis can reveal. First, AHP was the dominant method in 20 of 34 groundwater studies (59%), yet the meta-regression (Table 10) shows that AHP-only frameworks achieve a mean AUC of 0.748 significantly lower than the ML mean of 0.860 confirming that the most widely used groundwater mapping method is not the most accurate one. Second, moderate groundwater potential zones dominated the classified maps in 19 of 34 studies (56%), accounting for 47–75% of mapped areas a pattern consistent with AHP's central-weighting tendency rather than genuine spatial heterogeneity in hydrogeological conditions. Third, and most critically, not a single one of the 34 groundwater studies cited an SDG 6 target or linked their groundwater potential classification to national water supply monitoring data confirming that despite groundwater mapping being the dominant application in the 2021–2026 corpus, its policy connectivity remains entirely undeveloped. These three findings collectively identify the groundwater mapping sub-field as the highest-priority target for methodological upgrading and policy integration in the next generation of geospatial land and water resource management research.

3.15 Case studies

3.15.1 Land management case study

The case studies reviewed in this paper emphasize the diversity of land management practices across different regions, reflecting variations in socioeconomic, environmental, and institutional contexts (Kuemmerle, 2024). These studies reveal that land-use strategies are strongly context-dependent and determined by local resource accessibility, governance structures and technological adoption. For example, GIS-based planning systems applied in resource-constrained regions of Costa Rica emphasize probabilistic and data-driven

approaches to land-use decision-making(Mende et al., 2007). Similarly, studies from Vietnam highlight the necessity of technological advancements and capacity building to strengthen land management efficiency(Phạm Thị Thu Hường et al., 2023). In Ukraine, land inventory systems are recognized as critical policy instruments for enhancing land governance and supporting strategic planning (National University of Life and Environmental Sciences of Ukraine et al., 2020). However, Lithuania has demonstrated innovative approaches by developing business models for managing abandoned agricultural land (Lankauskienė et al., 2024). Moreover, sustainable land management increasingly incorporates interdisciplinary approaches, including hydrotechnical and climate-resilient strategies. These strategies extend beyond traditional land and water management practices by incorporating scientific advancements and cross-disciplinary knowledge to address complex environmental challenges (Leucuta & Halbac-Cotoara-Zamfir, 2016).For example, studies on climate adaptation strategies, including strengthening crop albedo under irrigation, have demonstrated the potential of land management practices to mitigate climatic extremes (Hirsch et al., 2017).

Real-world examples of effective land management are apparent in institutional and community-based systems. The management of waqf (endowed) rice fields in Indonesia illustrates how systematic and thorough land-use practices can accomplish sustainable productivity(Jamal et al., 2022). Additionally, the function of information systems and governance frameworks, especially in the public sector, underscores the significance of land tenure security, rights protection mechanisms, and collaborative decision-making processes (Rivera & Casias, 2001).Nevertheless, numerous obstacles remain, especially in regions where obsolete data systems and a lack of comprehensive land inventories hinder effective planning and investment. For example, constraints in land information systems in specific countries limit the development of strategic land-use plans and diminish the efficiency of resource allocation ((National University of Life and Environmental Sciences of Ukraine et al., 2021).

Economic instruments also play an important role in land management. In Kazakhstan, cadastral-based land taxation has been examined as a mechanism to support agricultural development and improve land-use efficiency (Ualiyeva & Syzdykova, 2021). These examples underscore the significance of integrating economic, technological, and institutional frameworks in land management strategies, emphasizing the necessity for a transition toward innovative, adaptive, and data-driven land management systems considering increasing resource scarcity. Although several techniques are region-specific, shared insights encompass

the importance of geospatial technologies, integrated planning frameworks, and stakeholder collaboration. These findings offer valuable guidance for developing sustainable land-use strategies at both the national and global levels. Across the 15 land management studies in the systematic review corpus, no study replicated the institutional-geospatial coupling evident in the most effective international cases described above confirming that technology adoption without governance integration is the defining gap of the 2021–2026 land management literature.

3.15.2 Water management case study

The combination of RS and GIS improves the comprehension of water systems by facilitating the acquisition of spatially detailed and near-real-time data. This combination enables a wide range of applications, including hydrological modelling, flood risk assessment, irrigation planning, and water resource monitoring (Patel et al., 2020). Despite their established effectiveness, differences persist in the adoption of advanced geospatial technologies across regions. For example, multispectral data from the Landsat series have been widely utilized in developed countries for the long-term monitoring of water resource dynamics. However, the implementation of more advanced and high-resolution geospatial technologies continues to be restricted in multiple regions, indicating a gap in technological implementation (Tarate et al., 2024).

Geospatial technologies have also been effectively implemented in large-scale water infrastructure projects, such as the South–North Water Diversion and Three Gorges projects, to enable planning, monitoring, and resource optimization. At the same time, these systems are equally effective in small-scale and localized water management applications. Geospatial tools serve a crucial role in enabling efficient data collection, analysis, and sustainable utilization of water resources. While continued progress and wider adoption of innovative technologies are needed, the present applications of RS and GIS have already shown considerable advances in water resource management across diverse environmental and socio-economic contexts. Of the 40 water management studies in the systematic review, none reported demand-side water governance data alongside their geospatial supply-side mapping a gap that the international case evidence above shows is precisely what separates monitoring from management.

3.15.3 Integrated land and water management case study

Integrated Land and Water Management (ILWM) promotes the collaborative management of land and water resources to achieve sustainable development while preserving the ecological balance. This framework emphasizes the interconnections among natural resources, socioeconomic factors, and environmental processes. To facilitate ILWM, geospatial technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) are progressively employed because of their ability to offer comprehensive spatial data, multitemporal analysis, and decision-support capabilities (Reddy, 2018b). Geospatial technologies have served a vital role in addressing real-world ILWM challenges through various case studies. For example, in southwestern Uganda, the integration of local knowledge with scientific analysis was accomplished through geospatial data and community-based resource mapping, thereby supporting sustainable land management practices ((Nabwire & Nyabenge, 2006)). Similarly, RS and GIS have been implemented for watershed prioritization in the Son–Karamnasa interfluves, enabling effective planning and management of land and water resources (Kumar et al., 2019).

These cases demonstrate the efficacy of geospatial techniques in enhancing ILWM through improved spatial analysis, resource assessment, and decision-making processes. By integrating diverse datasets and supporting participatory approaches, geospatial technologies substantially enhance the efficiency and sustainability of land and water management strategies in agriculture. Geospatial technologies are a critical element of ILWM frameworks, delivering powerful tools for data integration, analysis, and informed decision-making, thus contributing to sustainable resource management and long-term environmental resilience. The thematic evidence across all domains synthesized from 59 studies (Table 7) and supported by datasets documented in Tables 12–18 is brought together in Section 4, where the comparative performance of analytical frameworks (Table 10), identified research gaps (Table 19), and methodological limitations (Table 20) are discussed alongside concrete priorities for future geospatial research. Of the 59 reviewed studies, only 6 (10%) achieved genuine land-water integration within a single analytical framework, and all 6 covered catchments smaller than 500 km² confirming that the integrated approaches documented in international case literature have not yet been replicated at the basin or national scale in the 2021–2026 geospatial corpus.

4. Discussion

The 59.2% rise in publication output between 2021 and 2025, peaking at 1,735 articles in 2025, reflects a period of unusually rapid methodological expansion in the field. This growth coincides with three converging pressures: the post-COVID-19 disruption of field-based monitoring, which accelerated the adoption of satellite-derived alternatives; the second implementation phase of the UN Sustainable Development Goals (2016–2030), which elevated the demand for spatially explicit evidence in national reporting; and the mainstreaming of cloud-based processing platforms, such as Google Earth Engine and deep learning frameworks, in remote sensing from approximately 2020 onward. The concentration of output in China and the United States together accounting for the majority of Cluster 1 (2,276 documents; total link strength 574,316) reflects both the availability of high-resolution national geospatial datasets and sustained public investment in AI and environmental monitoring infrastructure. However, a more notable finding is the disproportionate citation impact of smaller contributors: Kenya (65.63 citations per document), Ecuador (39.00), and South Africa (36.24) substantially outperform their output share, suggesting that geospatial studies addressing acute resource stress in data-scarce regions attract stronger international attention than their publication volume would imply.

The dominance of groundwater potential zone mapping (39% of the systematic review corpus) aligns with the global water scarcity narrative but also reflects a methodological maturity effect: AHP-based multi-criteria frameworks have reached sufficient standardization that replication across new study areas is relatively straightforward. This contrasts with the pattern identified by Tarate et al. (2024), who noted that irrigation water management, a domain requiring dynamic, multi-season datasets, remains underserved by geospatial systematic reviews despite its direct SDG relevance. The meta-regression results of the present study provide a specific explanation for this gap: only 39.4% of the variance in model accuracy (ROC-AUC) was explained by the field validation point count ($R^2 = 0.394$), and a mere 9.4% by the thematic input layer count ($R^2 = 0.094$). This means that studies adding more layers or more validation points do not reliably produce more accurate models; the decisive factors are sensor resolution, method family selection, and geological context, none of which are well captured by the bibliometric indicators most commonly used to compare studies. This implies that current review practice, including this one, is better at mapping what has been done than at explaining why some approaches work and others do not.

The most practically consequential finding was the consistent performance advantage of machine learning and ensemble methods over AHP-only frameworks across all five within-study direct comparisons (mean ROC-AUC: 0.748 vs 0.860; vote-counting directional proportion: 100%). This gap approximately a 15% improvement in discriminative accuracy translates directly into better-targeted borehole siting and recharge zone identification in South Asian and African settings, where groundwater stress is most acute. However, the geographic heatmap (Fig.12) shows that AHP/MCDA remains the dominant approach in precisely these regions, whereas ML-based methods are concentrated in North America and parts of South Asia with stronger computational infrastructure. This disconnect between the demonstrated performance advantage and regional adoption pattern represents the most pressing translation gap in the field.

Several limitations reduce the generalizability of these conclusions. First, the analysis is confined to the 2021–2026 window; a two-phase comparison with a 2000–2020 baseline dataset, which this study did not construct, would clarify whether the observed AHP-to-ML transition represents a genuine field-wide shift or an artifact of the temporal scope. Second, the regression analysis was based on 10 studies with reported AUC values, which is sufficient to identify directional trends but too small for robust inferential conclusions. Third, the systematic review corpus of 59 studies is geographically concentrated in South Asia and Africa, which reflects genuine research intensity in those regions but limits the transferability of method-performance conclusions to Arctic, arid or island settings. Fourth, 13 of the 59 studies used static or single-epoch datasets in contexts where multi-temporal data would have been methodologically more appropriate. These studies were retained in the synthesis but contributed to indicative rather than confirmatory evidence. Addressing these limitations requires prospective registration of future reviews, adoption of multi-epoch satellite archives as a minimum design standard, and benchmark validation datasets stratified by bioclimatic zone, none of which currently exist in an accessible, community-maintained form.

Fifth, the bibliometric component relies on the Dimensions API as the primary data source. Although cross-validation against Scopus (Spearman $\rho = 0.92$) and WoS ($\rho = 0.89$) confirms strong concordance in country-level rankings, Dimensions' broader indexing of open-access and grey literature may inflate publication counts relative to Scopus-only analyses. Future bibliometric replications should consider a full three-database merge using a validated deduplication protocol to quantify this bias.

A direct comparison of geospatial analytical approaches reveals four performance gradients relevant to practitioners. First, direct within-study comparisons reveal that AHP-only frameworks AHP is accessible, interpretable, and applicable in data-scarce settings (mean AUC=0.748) but is sensitive to expert weighting subjectivity and consistently underperforms ML in within-study comparisons; ML achieves mean AUC=0.860 but requires larger training datasets and produces outputs that reduce stakeholder interpretability. Second, studies using multi-temporal archives: static single-epoch data identify current conditions but cannot quantify change trajectories; studies using archives spanning ten or more years consistently produced richer, policy-relevant findings. Third, SAR-optical fusion enables single-sensor studies are reproducible but miss subsurface groundwater dynamics, whereas SAR–optical fusion captures both surface and subsurface indicators at the cost of increased preprocessing complexity. Fourth, and most practically accessible, AHP-only vs AHP-hybrid: the addition of TOPSIS, SWAT calibration, or flood modelling to an AHP framework raises mean AUC from 0.748 to 0.815 a 9% accuracy gain with no increase in data requirements and represents the most accessible near-term methodological upgrade for South Asian and African practitioners who currently rely on AHP-only frameworks.

4.1 Challenges in land and water management

As emphasized in published research, the management of land and water resources continues to be a complex challenge (Schmidt et al., 2011). Growing population pressure, rapid urbanization, and conflicting requirements for natural resources have intensified stress on land and water systems, making sustainable management more difficult (Goran and Holland, 2001). Conflicts frequently arise among agricultural expansion, industrial development, and environmental conservation, complicating attempts to achieve balanced resource utilization. Climate change intensifies these challenges by increasing water scarcity, accelerating land degradation, and altering hydrological processes, thereby introducing uncertainty into resource management strategies (Moges 2023). Furthermore, institutional and governance-related constraints, such as fragmented policies, weak coordination among stakeholders, and limited integration of traditional knowledge systems, significantly hinder the effective implementation of management frameworks (Sukereman et al., 2015). Socio-economic inequalities and restricted involvement of local communities, particularly marginalized groups, lead to inefficiencies in decision-making processes (Mohan et al., 2020). For instance, women, who play a crucial role in community-based knowledge systems, are frequently underrepresented in

land and water management initiatives, causing gaps in comprehensive and context-specific solutions. Similarly, matters concerning land tenure systems, including tribal land policies, can limit equitable access to resources and compromise effective water management (Joshi et al., 2021).

Moreover, insufficient legislative frameworks and poor coordination among institutions and communities continue to limit the effective implementation of integrated water resource management (IWRM) approaches (Sukereman et al., 2015). These challenges demonstrate the necessity of more cohesive governance frameworks and enhanced policy alignment achieved through integrated, adaptive, and inclusive approaches that combine technological innovation with strong institutional support and stakeholder collaboration. Priority should be placed on participatory approaches, incorporating traditional knowledge, and empowering vulnerable groups to ensure equitable and sustainable outcomes. As highlighted in the literature, integrated approaches offer more comprehensive and efficacious solutions for managing land and water resources amid escalating environmental and socioeconomic pressures (Moges, 2023). Sustainable land and water resource management depends on collaborative initiatives across social, institutional, and technological dimensions supported by inclusive governance and continuous policy innovation.

Five concrete policy integration steps are recommended based on the evidence synthesized in this review. First, national SDG reporting agencies should adopt a minimum geospatial evidence standard requiring that all groundwater potential or LULC assessments submitted for SDG 6 and SDG 15 monitoring report $\text{ROC-AUC} \geq 0.80$ with a minimum of 50 field-validated points the threshold above which this study demonstrates reliable model accuracy. Second, Ministries of Water Resources in South Asia and Sub-Saharan Africa should replace AHP-only frameworks with AHP-hybrid or ML-enhanced designs in national groundwater potential mapping programmes, prioritizing Google Earth Engine and Sentinel-2 (10 m) to remove data access barriers. Third, IWRM frameworks should explicitly integrate demand-side water governance indicators stakeholder participation metrics and cross-sectoral policy coherence scores alongside supply-side geospatial outputs, both identified as underrepresented in the current corpus. Fourth, the UN-GGIM Integrated Geospatial Information Framework should be updated to include a minimum reporting standard for geospatial policy evidence, analogous to the CONSORT standard in clinical research, requiring explicit declaration of spatial resolution, temporal coverage, validation dataset size, and

software version. Fifth, development finance institutions funding land and water management programmes should require beneficiary countries to adopt multi-temporal satellite monitoring (minimum five-year archive) as a performance evaluation tool, replacing single-epoch status assessments that cannot capture trend direction.

4.2 Research gaps and limitations

4.2.1 Integration gaps

Technological deficiencies persist in constraining the effective adoption and utilization of advanced geospatial tools in land and water resource monitoring. While emerging technologies such as Unmanned Aerial Vehicles (UAVs), LiDAR, and hyperspectral imaging demonstrate significant potential for high-resolution soil and water quality analysis, their large-scale operational deployment remains limited. For example, the integration of UAV-based LiDAR and hyperspectral data has enhanced prediction accuracy; nevertheless, its implementation is still at an early stage, especially in automated and real-time monitoring systems (H. Liu et al., 2021).

Similarly, the use of Internet of Things (IoT)-based sensor networks for uninterrupted in-situ monitoring has not been widely adopted, suggesting a gap in real-time environmental data acquisition. Although cloud-based platforms such as the Google Earth Engine (GEE) have enabled the efficient processing of large geospatial datasets for applications including flood mapping, land-use classification, and water quality assessment, their full potential remains underutilized (Amani et al., 2020). Multiple studies still depend on manual or semi-automated workflows, with restricted deployment of completely autonomous systems that integrate remote sensing and ground-truth data for scalable and timely analysis.

Furthermore, artificial intelligence and machine learning (AI/ML) models, such as Random Forest, Support Vector Machines (SVM), and gradient-boosted decision trees (GBDT), have shown high accuracy in classification and prediction tasks using geospatial data (Feizizadeh et al., 2023). However, the limited integration of in-situ and crowdsourced data for calibration and validation reduces the robustness and reliability of these models.

Data fusion constitutes another critical challenge, as only a few studies have successfully integrated satellite imagery, field observations, and participatory datasets into a unified framework. Furthermore, variations in the spatial and temporal resolutions across

datasets constrain comprehensive analyses. High-resolution data are often costly or inaccessible, while temporal inconsistencies between land and water datasets impede coordinated evaluations. The identified research gaps, associated limitations, and potential future directions in geospatial technologies for environmental and resource management is presented in Table 19. Addressing these gaps requires the development of integrated, automated, and scalable geospatial frameworks that combine advanced sensing technologies, real-time data acquisition, and robust analytical models. To advance beyond these general observations, we propose four specific and actionable research directions. (1) The development of a standardized Real-Time Geospatial Monitoring Framework (RT-GMF) is recommended. This framework integrates IoT sensor networks, Google Earth Engine cloud processing, and machine learning-based anomaly detection to facilitate the continuous automated reporting of land–water status at the watershed scale. A prototype could be implemented in data-scarce regions, such as the Ethiopian Rift Valley or the Indo-Gangetic Plain, where data deficiencies are most pronounced. (2) A two-phase bibliometric replication utilizing a 2000–2020 baseline dataset from the Dimensions API would enable statistically robust before-and-after comparisons of research trajectories, thereby assessing whether the post-2020 AI-driven surge constitutes a structural shift or merely a citation artifact. (3) A Policy-Geospatial Integration Scorecard is proposed, adapted from the OECD Water Governance Indicator framework, to evaluate the extent to which geospatial study recommendations are incorporated into national SDG reporting. This tool transforms the current qualitative gap between research and policy into a quantifiable index. (4) Future systematic reviews in this field should adopt a prospective registration protocol (e.g., PROSPERO or OSF registration) and employ standardized quality assessment rubrics specifically tailored to geospatial studies. These rubrics should build on the five-dimensional quality tool piloted in this review (spatial resolution bias, temporal consistency, model validation integrity, ground truth reliability, and selection bias) to enhance cross-study comparability.

4.2.2 Methodological limitations

Methodological limitations remain a major obstacle in land use, water quality, and drought assessment studies, affecting the comparability, reliability, and generalization of findings. One of the primary issues is the absence of standardization, as a wide variety of methods have been employed for land-use classification, water quality monitoring, and drought index computation (Bhaga et al., 2020). Methodological differences across studies particularly

in spatial and temporal contexts render it challenging to compare results and draw consistent conclusions, and substantial variability exists in the determination of thresholds, indices, and accuracy assessment techniques. For example, drought analysis outcomes differ considerably depending on whether indices such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), or NDVI-based indicators are used. These variations are also affected by the choice of reference periods and statistical distributions (Zang et al., 2020). Even commonly recognized indices, such as the SPI and SPEI, are subject to methodological uncertainties, particularly in terms of distribution fitting and parameter estimation.

In addition to standardization issues, many studies rely heavily on descriptive mapping approaches, with limited use of predictive modelling techniques. Advanced analytical methods, such as Multi-Criteria Decision Analysis (MCDA), spatial statistics, and machine learning, remain underutilized despite their demonstrated ability to enhance analytical precision and support scenario-based decision-making (Valiya Veetil & Mishra, 2020). Additionally, a prevailing focus on single indices often fails to capture the complex interactions between land, water, and climate systems, whereas integrated and multivariate approaches provide greater insight but are less frequently applied.

Verification and evaluation also have major limitations. Numerous studies lack sufficient in-situ observations or ground-truth data to validate their remote sensing outputs, reducing the reliability of their findings. Moreover, comparative analyses of different modelling approaches, such as Random Forest, Support Vector Machines, and deep learning techniques, are limited, and the absence of standardized benchmark datasets further constrains robust evaluation (Lines et al., 2022). The methodological limitations, their effects on the study outcomes, and suggested enhancements are presented in Table 20. To address these limitations, three specific measures are proposed. First, studies from South Asia and Africa should report in-country model accuracy benchmarked against international standards, to quantify the performance penalty of data scarcity and justify methodological investment in those regions. Second, multi-index drought and erosion assessments integrating at least SPI combined with NDVI-based Vegetation Condition Index (VCI) with stated uncertainty bounds should replace single-index approaches as the standard for policy-relevant outputs. Third, all future groundwater potential mapping studies should report SHAP-based feature importance scores

alongside AUC values, enabling cross-study comparison of conditioning factor contributions independent of method family and improving stakeholder interpretability of model outputs.

4.3 Future trends and innovations in geospatial techniques

4.3.1 Advanced remote sensing technologies

Despite the rapid advancement and expanding applications of remote sensing technologies, their integration into broader sectors, such as energy systems and advanced agricultural management, remains in its early stages. This limitation presents significant opportunities for technological innovation and interdisciplinary research, particularly in achieving Sustainable Development Goals (SDGs) related to sustainable resource utilization and environmental protection (Kosta et al., 2020). Furthermore, advanced remote sensing systems, such as Synthetic Aperture Radar (SAR), are gaining increasing attention because of their capability to operate under all-weather conditions and provide consistent, high-resolution data. These systems have demonstrated substantial potential for monitoring environmental changes, assessing land surface dynamics, and detecting and preserving archaeological heritage ((Jiao, 2024; Sanders & Masri, 2016). However, several challenges persist in integrating advanced remote-sensing technologies into comprehensive resource management frameworks. These include issues related to data accessibility, interoperability, processing complexity, and the need for real-time analysis. Addressing these challenges is essential to fully exploit the capabilities of modern remote sensing systems, and the continued development and integration of advanced remote sensing technologies in combination with GIS and GPS will be instrumental in enhancing sustainable land and water resource management and supporting data-driven decision-making across multiple sectors.

4.3.2 Integration of AI and machine learning

Three emerging AI paradigms are beginning to reshape geospatial research beyond the conventional ML methods reviewed in this study. Geospatial Artificial Intelligence (GeoAI) integrates spatial reasoning with deep learning architectures specifically graph neural networks and attention-based transformers enabling the modelling of non-Euclidean spatial relationships such as aquifer connectivity and watershed topology that conventional ML cannot capture. Foundation models, including geospatial large language models and vision transformers pre-trained on satellite imagery archives (e.g., the IBM–NASA Prithvi model trained on Harmonized Landsat–Sentinel-2 data), offer the potential for zero-shot and few-shot geospatial

analysis that could substantially reduce the labelled training data requirements currently constraining ML adoption in data-scarce African and South Asian settings. Geospatial digital twins dynamic, data-linked virtual replicas of real-world watersheds or urban catchments combine real-time IoT sensor feeds, satellite imagery, and physics-based hydrological models into a single interactive decision-support environment. None of the 59 studies in this systematic review adopted any of these three frameworks, confirming that the 2021–2026 corpus, while representing the current frontier of practice, has not yet incorporated the leading edge of methodological development. Among the 59 reviewed studies, 14 (24%) applied ML or ensemble methods predominantly Random Forest and logistic regression and their comparative performance is documented in Table 21. None adopted GeoAI, foundation models, or digital twin architectures, confirming that the conventional ML frontier described in this corpus and the three emerging AI paradigms described above are separated by at least one generation of methodological development. This gap is not merely technical: the geospatial training data, computational infrastructure, and institutional capacity required to operationalize GeoAI, and foundation models remain largely absent from the South Asian and African settings that dominate the 2021–2026 literature. Closing this gap represents the most important single opportunity for the next generation of geospatial land and water resource management research.

4.3.3 Big data analytics in geospatial studies

Big Data Analytics encompassing distributed computing frameworks such as Apache Spark (Shangguan et al., 2017), cloud-native geospatial processing platforms such as Google Earth Engine, and multi-source data fusion pipelines is widely cited as the next operational frontier for land and water resource monitoring (Li et al., 2020; Al-Yadumi et al., 2021). The integration of Remote Sensing, GIS, and AI with Big Data infrastructure theoretically enables the efficient processing, analysis, and interpretation of large and complex spatial datasets at scales that conventional desktop workflows cannot achieve (Rane et al., 2023). A summary of representative Big Data applications integrated with geospatial technologies across resource management domains is presented in Table 22. However, the systematic review conducted in this study reveals a critical discrepancy between bibliometric prominence and operational adoption: none of the 59 reviewed studies applied a Big Data framework explicitly. The corpus relied predominantly on single-scene or multi-date satellite composites processed in desktop GIS environments, confirming that despite Big Data appearing as a co-occurring keyword in Cluster 4 of the bibliometric network (Fig. 6), it has not yet penetrated the operational research practice of the 2021–2026 land and water management literature. This gap is not primarily technical Google Earth Engine and open-access Sentinel archives already provide the data

infrastructure required for Big Data geospatial workflows but institutional: the resource-constrained research settings that dominate the corpus (South Asia, Sub-Saharan Africa) lack the computational training capacity and community-maintained benchmark datasets needed to make Big Data approaches reproducible and comparable across study sites. Addressing this gap requires coordinated investment in geospatial capacity building and the development of standardized cloud processing pipelines tailored specifically to land and water resource monitoring in data-scarce regions.

4.3.4 Real-time monitoring frameworks

Real-time geospatial monitoring remains the most critical unmet operational need identified across the 59 reviewed studies. A standardized Real-Time Geospatial Monitoring Framework (RT-GMF) is proposed, integrating IoT sensor networks for in-situ data acquisition, Google Earth Engine cloud processing for near-real-time satellite analysis, and machine learning-based anomaly detection for automated alert generation. The framework would operate at the watershed scale, providing sub-daily reporting for flood and drought triggers, monthly LULC change updates, and annual groundwater trend assessments. Prototype implementation is recommended in the Ethiopian Rift Valley and the Indo-Gangetic Plain regions where geospatial research is concentrated, groundwater stress is most acute, and data deficiencies are most pronounced.

4.3.5 Explainable AI for geospatial decision-making

A critical gap in the current corpus is the complete absence of Explainable AI (XAI) approaches. Of the 59 reviewed studies using ML methods, none reported SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) outputs alongside conventional accuracy metrics. Policymakers and water resource managers require interpretable model outputs to justify borehole siting, recharge investment, and flood evacuation decisions a black-box Random Forest achieving $AUC = 0.910$ is insufficient for governance accountability. Future studies should be required to report SHAP feature importance scores as a minimum output standard, enabling both cross-study reproducibility and stakeholder trust in geospatial model recommendations.

4.3.6 Climate-resilient geospatial resource management

Climate change is progressively invalidating the static baseline assumptions embedded in current geospatial models. Groundwater potential zone maps calibrated on 2015–2020 recharge patterns may be inaccurate by 2035 under SSP2-4.5 precipitation trajectories in the Sahel, Horn of Africa, and South Asian semi-arid zones precisely the regions where AHP-based mapping is most concentrated in this review. Future geospatial frameworks must integrate

CMIP6 climate projections as dynamic conditioning layers, updated on a five-year cycle, to maintain planning relevance. Studies coupling climate-informed LULC projections with hydrological sensitivity analysis represent the highest-priority research design for the next generation of geospatial land and water resource management investigations.

5. Conclusion

This study combined a bibliometric analysis of 335 peer-reviewed articles (2021–2026) with a PRISMA-based systematic review of 59 included studies to characterize the current state of geospatial methods research for land and water resource management. Five principal conclusions emerged from the integrated analysis.

First, research output grew by 59.2% between 2021 and 2025, peaking at 1,735 publications in 2025, driven by the convergence of post-COVID-19 remote monitoring demand, the second phase of UN SDG implementation, and mainstreaming of cloud-based geospatial platforms. This growth is global in reach but uneven in depth: China and the United States account for the largest share of output and collaboration, while Kenya (65.63 citations per document), Ecuador (39.00), and South Africa (36.24) demonstrate that studies addressing acute resource stress in data-scarce settings achieve disproportionate citation impact.

Second, groundwater potential zone mapping dominated the systematic review corpus (39% of studies), with AHP-based multi-criteria frameworks being the most widely applied method. This methodological concentration reflects practical accessibility rather than optimal performance: within-study comparisons consistently show that machine learning and ensemble methods outperform AHP-only frameworks (mean ROC-AUC: 0.860 versus 0.748), yet AHP remains dominant in precisely the South Asian and African settings where groundwater stress is most severe. Closing this adoption gap represents the most tractable near-term improvement available in the field.

Third, model accuracy is not well predicted by the design parameters most reported in the geospatial studies. The validation point count explained only 39.4% of the AUC variance ($R^2 = 0.394$), and the thematic input layer count explained only 9.4% ($R^2 = 0.094$). The decisive factors—sensor resolution, method family, and local geological context—are rarely standardized or reported consistently, which limits cross-study comparison and evidence synthesis.

Fourth, LULC-driven water resource degradation is the most evidence-dense directional finding in the corpus: 92% of comparative studies confirm that urban and agricultural expansion measurably reduces groundwater levels, water body extent and groundwater quality. This finding is robust across 11 of the 12 studies spanning Bangladesh,

India, Zimbabwe, Ghana, and Kenya, and directly supports the SDG 6 (clean water) and SDG 15 (land degradation neutrality) monitoring frameworks.

Fifth, the most persistent structural weakness across the corpus is the reliance on static, single-epoch datasets in contexts that require multi-temporal analysis. Four of the 14 quality-assessed studies were rated as having Moderate or High temporal bias risk; studies using archives spanning ten or more years consistently produced richer, more policy-relevant findings than their static counterparts.

Three specific priorities should guide future research. A two-phase bibliometric replication using a 2000–2020 baseline dataset would clarify whether the observed AHP to ML transition represents a genuine field-wide shift or an artifact of the 2021–2026 period. Community-maintained benchmark validation datasets stratified by bioclimatic zones are needed before cross-study accuracy comparisons become meaningful. Prospective registration of geospatial systematic reviews, currently absent from the field, would improve protocol transparency and reduce publication bias toward positive model performance outcomes. The 2030 SDG agenda requires that geospatial evidence evolve from descriptive mapping to predictive, policy-integrated, and reproducible decision tools the three pillars around which the identified gaps, the proposed frameworks, and the future priorities of this review are explicitly organized.

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Declarations

Ethical Approval

This article does not contain any studies involving human participants or animals performed by any of the authors. Therefore, ethical approval was not required for this study.

Consent to Participate

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1538 The authors used AI-assisted language tools solely for grammatical corrections,
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1542 **Authors Contributions**

1543 **Ajay Prakash M:** Conceptualization, Supervision, Data curation, Methodology,
1544 Review & Editing **Ragunath K.P:** Methodology, Formal analysis, Investigation, Writing -
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1546 & Editing **Sivamurugan A.P:** Review & Editing **Vanitha. G:** Review and& Editing **Fawaz**
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Table 1 . Comparison of three bibliographic databases used in this study. Dimensions API served as the primary bibliometric data source, and Scopus and WoS were used for cross-validation.

Feature	Dimensions API (primary)	Scopus (cross-validation)	Web of Science (cross-validation)
Coverage	> 140 million publications; broad multidisciplinary scope including grey literature and preprints	~90 million records; strong in STEM, social sciences	~90 million records; strong in STEM, natural sciences
Access model	Open-access metadata; free API access for researchers	Subscription-based; institutional access required	Subscription-based; institutional access required
API availability	Full programmatic API (bulk retrieval); used for reproducible dataset construction	Limited API; primarily web interface	Limited API; primarily web interface
Use in this study	Primary bibliometric dataset; all trend, co-authorship, and keyword analyses	Cross-validation: 200-record random sample confirmed 94% overlap with Dimensions results	Cross-validation: co-authorship network structure confirmed consistent with Dimensions output
Limitation	May index some lower-impact sources not in Scopus/WoS	Subject to subscription restrictions; not all geospatial journals fully indexed	Smaller coverage of non-English and open-access sources

* API: Application Programming Interface. Cross-validation Spearman rank correlations: Dimensions vs. Scopus $\rho = 0.92$; Dimensions vs. WoS $\rho = 0.89$ (top-10 country rankings). Record overlap was confirmed for a random sample of 200 records: 94% were present in Scopus, and 91% in WoS.

Table 2. Sequential data filtering pipeline for bibliometric analysis. All three publication counts (7,104; 2,500; 335) are shown in this table. The final dataset used for all analyses included 335 participants.

Step	Action / Filter applied	Records retained	Records excluded	Cumulative n
Step 1	Initial Boolean search: "Geospatial Methods AND Land AND Water Resource Management" applied to Title + Abstract fields; Dimensions API; search date 26 March 2026; all document types; all years; all languages	7,104	—	7,104
Step 2	Filter: document type = "Article" only (conference papers, reviews, book chapters, editorials excluded); publication years restricted to 2021–2026	2,500	4,604	2,500
Step 3	Filter: language = English only (all non-English articles excluded)	335	2,165	335
Final dataset	English-language peer-reviewed articles, 2021–2026, geospatial focus on land and water resource management — used for all bibliometric analyses	335	—	335

** Step 3 excluded 2,165 non-English articles from the 2,500-record intermediate dataset. The large proportion of non-English records (86.6% of 2,500) is consistent with Dimensions' broad global indexing, which includes substantial Chinese, Arabic, and Spanish-language publication outputs not captured in Scopus or Web of Science to the same degree.*

Table 3 .Annual publication output of geospatial methods in land and water resource management research, 2021–2026. Source: Dimensions API (n = 335 final dataset filtered to English-language articles; n = 7,104 for all document types used for trend count). *2026 = partial year, January–March 2026 only; excluded from year-on-year growth calculations.

Year	Total publications (n)	Year-on-year change (n)	Year-on-year change (%)	Notes
2021	1,090	—	—	Baseline year
2022	1,378	+288	+26.4%	Post-COVID research recovery
2023	1,276	−102	−7.4%	Consolidation period
2024	1,376	+100	+7.8%	Steady recovery
2025	1,735	+359	+26.1%	Peak year; AI/ML mainstreaming
2026*	249	—	—	Partial year: January–March 2026 only; search conducted 26 March 2026
Total (2021–2025)	6,855	—	+59.2% (2021→2025)	Full-year data only

* 2026 = partial year (January–March 2026 only); excluded from all year-on-year growth calculations and trend analyses. Overall cumulative growth (2021–2025): +59.2% (1,090 to 1,735 publications). The 2026 annualized projection (~996 publications based on Q1 output) is provided for contextual reference only and does not constitute a confirmed trend, as it is based on a projection. AI/ML = artificial intelligence/machine learning.

Table 4. Pre-specified inclusion and exclusion criteria applied across the eight eligibility dimensions. The criteria were applied sequentially at each screening stage (title → abstract → full text).

Criterion category	Inclusion criteria	Exclusion criteria
Publication type	Peer-reviewed original research articles and systematic/bibliometric reviews published in English	Conference abstracts, book chapters, grey literature, editorials, commentaries, non-peer-reviewed reports
Publication period	Studies published between 2021 and 2026 (5-year window capturing post-AI surge, SDG Phase 2, and post-COVID monitoring context)	Studies published before 2021 or after the search date of 26 March 2026
Study scope	Studies applying geospatial methods (GIS, remote sensing, spatial analysis) to land or water resource management tasks	Studies solely focused on climate modelling, crop yield, food security, or socioeconomic analysis without a geospatial component
Geographic scope	No geographic restriction; global studies accepted	Studies covering only indoor or laboratory-scale environments without field geospatial data
Language	English-language publications only	Studies published in languages other than English
Data sources	Studies using satellite imagery, aerial photography, DEM, field-collected spatial data, or secondary geospatial datasets (for example, SRTM, CHIRPS, GRACE)	Studies based exclusively on non-spatial survey data, laboratory measurements, or modelled outputs without spatial validation
Analytical methods	Studies applying at least one geospatial analytical technique: AHP/MCDA, RUSLE/USLE, SCS-CN, ML/DL spatial models, LULC classification, hydrological simulation (SWAT, HEC-HMS)	Studies using GIS only for cartographic display without any spatial analysis; pure statistical studies without a geospatial analytical component
Validation reporting	Studies reporting at least one quantitative outcome metric (accuracy, AUC, R ² , RMSE, NSE, Kappa, or equivalent) or qualitative field-based verification	Studies reporting no form of model validation or ground-truth verification whatsoever
Outcome relevance	Studies with outcomes directly applicable to land resource management (LULC, erosion, land degradation) or water resource management (groundwater potential, water quality, runoff, flood hazard)	Studies with outcomes exclusively applicable to non-environmental domains (e.g. urban transportation, building mapping, archaeology)

* MCDA = Multi-Criteria Decision Analysis; SWAT = Soil and Water Assessment Tool; HEC-HMS = Hydrologic Engineering Center – Hydrologic Modelling System; DEM = Digital Elevation Model; SRTM = Shuttle Radar Topography Mission; CHIRPS = Climate Hazards Group InfraRed Precipitation with Station; GRACE = Gravity Recovery and Climate Experiment.

Table 5. Staged screening protocol applied across three sequential screening rounds, followed by a separate post-screening quality appraisal.

Stage	Screening question applied	Action if NO
Stage 1 Title screening	Does the title indicate the use of geospatial methods AND a focus on land or water resource management	Exclude (record reason: off-topic)
Stage 2 Abstract screening	Does the abstract confirm: (a) peer-reviewed publication in English, 2021–2026; (b) at least one geospatial analytical method applied; and (c) study outcome linked to land or water management?	Exclude (record reason: insufficient scope / language / period)
Stage 3 Full-text eligibility	Does the full text: (a) report explicit inclusion/exclusion criteria or a defined study area? (b) Provide at least one validation metric for the model. (c) Use primary geospatial data (satellite, field, DEM)?	Exclude with reason (n = 77 excluded at full-text stage)
Post-screening QA appraisal (not a screening stage)	Does the study score Low or Moderate risk on ≥ 3 of the 5 QA dimensions (Table 6)? — Studies failing this threshold are retained but flagged; this step does not exclude studies.	Retain with quality caveat; flag for sensitivity analysis. No studies excluded at this stage.

* Inter-rater agreement was measured in Stage 2 (abstract) and Stage 3 (full-text). Kappa at Stage 2 = 0.87; Kappa at Stage 3 = 0.84. Both exceeded the 0.80 threshold for strong agreement (Landis & Koch, 1977). All disagreements were resolved by discussion; no third arbiter was required.

Table 6. Five-dimensional quality appraisal tool for geospatial systematic reviews. Each dimension is assessed independently and scored as Low, Moderate, or High risk based on the criteria below. Overall quality classification: High = Low/Moderate on $\geq 4/5$ dimensions; Moderate = Low/Moderate on $3/5$; Low = Low/Moderate on $\leq 2/5$.

QA Dimension	Criteria for Low Risk	Criteria for Moderate Risk	Criteria for High Risk
Q1: Spatial resolution bias	High-resolution sensor (≤ 10 m; Sentinel-2, Sentinel-1 SAR, NHD)	Moderate resolution (30 m; Landsat, ASTER)	Coarse resolution (> 250 m; MODIS) or unspecified
Q2: Temporal consistency	Multi-temporal archive ≥ 10 years; acquisition frequency matches process dynamics	Medium-term archive 3–10 years; partial temporal coverage	Static or single-epoch dataset; temporal mismatch with study process
Q3: Model validation integrity	ROC-AUC ≥ 0.80 and/or $R^2 \geq 0.75$ with independent test-set validation	Overall accuracy 75–90% without supplementary discriminant metric	No independent test set; AUC < 0.70 ; accuracy $< 75\%$; or no metric reported
Q4: Ground truth reliability	≥ 50 field-verified points from laboratory-certified or GPS-surveyed sources	Field data from Google Earth interpretation or 20–49 sampling points	< 20 field points or no primary field data; map-to-map validation only
Q5: Selection bias	Explicit, reproducible sampling strategy reported; representative coverage of study area	Partial sampling documentation; minor geographic clustering of validation points	No sampling strategy documented; cherry-picked or non-representative validation sites

** All quality assessments were conducted by two independent reviewers. Inter-rater agreement: $\kappa = 0.81$ (strong); discrepancies ($n = 12$ dimension-level disagreements across 59 studies) were resolved through discussion. The tool is available in Supplementary Material S2 as a replicable Excel-format scoring sheet for use in future geospatial systematic reviews.*

Table 7. Overview of the selected (included) studies illustrating the geographical coverage, data sources, analytical methods/models, research focus, validation approaches, and major findings in geospatial-based land and water resource assessment.

S.No	Author & Year	Study Area	Data Used	Method/Model	Study Focus	Validation	Key Findings
1	(Ozegin et al., 2024)	South and North-Central Nigeria	Landsat 8 OLI; SRTM DEM; soil maps (NGSA); rainfall (NASA-IDW); LULC, slope & LST; lineament data; borehole yield data	MCDA-AHP; 9 thematic layers (rainfall, slope, drainage density, lineament, geomorphology, soil, LULC, elevation, LST); pairwise weighting ($CR \leq 0.1$); weighted linear combination (WLC); GIS integration (ArcGIS); sensitivity analysis (SI); multicollinearity test (VIF)	Groundwater potential zone (GPZ) mapping; supports groundwater planning & management; integrates geoenvironmental factors; aids site selection for tube wells and resource utilization	Borehole validation (21 yield points) showing 90.5% agreement; linear regression validation ($R^2=0.911$) indicating high predictive accuracy; multicollinearity test ($VIF < 2.5$, tolerance > 0.4) confirming variable independence	Low–very low groundwater potential dominant (~61%); high–moderate zones ~42%; rainfall & lineament density most influential; strong model performance (90.5% agreement, $R^2=0.911$); reliable AHP ($CR=0.03$); suitable for groundwater planning
2	(Workie & Teku, 2025)	Beshilo Watershed, Northeastern Ethiopia, Amhara region	Landsat (TM/ETM+/OLI) for LULC & NDVI; SRTM DEM (30m) for slope & drainage; CHIRPS rainfall (2000–2023); FAO soil data; field surveys (57 sites); GPS gullies (671) & landslides (578); Google Earth validation	RUSLE model ($A=R \times K \times LS \times C \times P$); R (rainfall), K (soil), LS (slope), C (LULC), P (practice); GIS integration; Landsat-based LULC classification; NDVI analysis; FAO-based erosion severity classification; field inventory validation	Soil erosion hotspot mapping; land degradation assessment; identification of erosion drivers (slope, rainfall, LULC); integration of GIS, RS, and field data; supports sustainable land management (SLM) planning	Field validation (57 sites) with GPS-based gully/landslide data; strong spatial agreement with observed erosion features; comparison with literature; qualitative validation (no statistical metrics)	Very high soil loss (avg 68.3 t/ha/yr; max 1288); ~38% area under severe erosion; exceeds tolerance limits; cultivation dominant (73%) with low forest cover; severe vegetation degradation; erosion driven by slope, poor practices & soil condition; SLM measures required
3	(Bah Ntutuwouo et al., 2024)	Mbandjock, Central Cameroon (Haute Sanaga);	SRTM DEM (1 arc-sec); Landsat 8 (30 m); rainfall (2012–2022); soil data (texture/type);	AHP-based MCDA; 7 thematic layers (drainage, slope, LULC, rainfall, soil, geology, lineament); pairwise	Groundwater potential mapping; recharge factor analysis; identification of suitable zones for	AHP consistency check (λ_{max} , CI, $CR \leq 0.1$); matrix coherence validation; LULC	GPZ: very high (31.35%), high (15.15%), moderate (8.81%), low (43.12%), very low (1.57%); eastern zone most favorable; key factors—rainfall, lineament

		bordered by Yoko, Nanga-Eboko, Ntui, Nkoteng; crossed by Sanaga River; rural area with 15+ villages near Yaoundé	geological map; field data (ROI, Google Earth validation)	weighting (1–9 scale, CR check); supervised classification; GIS (ArcGIS 10.8) & RS (ENVI)	wells/boreholes; supports water resource planning and decision-making	classification accuracy assessment using reference data	density, gentle slope, permeable sandy-clayey soils
4	(Chuma et al., 2022)	Chisheke watershed located in Walungu territory in the vicinity of Kabare territory and the Kahuzi-Biega National Park (PNKB), in South Kivu province, eastern Democratic Republic of Congo	ASTER DEM (30 m); Landsat 7 & 8 (1989–2020); land cover (ESA/UCL); climate (CHIRPS, WorldClim); soil data (SOTERCAF, ISRIC); field survey (200 farmers)	RUSLE model (R, K, LS, C, P factors) with GIS (ArcGIS 10.4.1); NDVI-based C-factor; DEM-based LS-factor; SVM classification for LULC	Soil erosion estimation (RUSLE); LULC change impact analysis; farmer perception assessment; supports sustainable soil conservation planning	Classification accuracy (89.8–95%) & Kappa; confusion matrix; rainfall calibration ($R^2=0.72$)	Soil loss avg. 24 t/ha/yr (0–400); highest in settlements & bare land; agriculture expanded, forest declined; key drivers—deforestation, slope, poor management; NDVI linked to tea productivity
5	(Valencia-Ortiz et al., 2026)	Sonoran Basin and Range (SBR) ecoregion in Arizona	Sentinel-1 (SAR, 10 m, ± 12 days) and Sentinel-2 (± 5 days); Landsat-8/9 LST (30 m); ECa (DuaLEM-1S, 153 ha); MERIT DEM; 361 soil	RFE feature selection; Logistic Regression (LR); optimized & simplified models (OM, SM); SMOTE (class imbalance); hyperparameter tuning	Soil salinity prediction; ML + geospatial integration; 10 m salinity mapping; LST & ECa analysis; soil management & decision support	K-fold cross-validation; precision, recall, F1-score; ROC-AUC (0.73); confusion matrix; bootstrap	Accuracy ~ 0.68 ; ROC-AUC 0.73; SMOTE improved recall (21–32% $\rightarrow$ 61–68%); AI & Sentinel-2 key predictors; 10 m salinity maps; LST comparable to AI; reliable for fine-scale monitoring

			samples (0–15 cm); climate data (WorldClim, AI, PET, groundwater depth); soil properties (SoilGrids – clay, silt, sand)	(GridSearchCV, L2/ElasticNet)		resampling; Spearman correlation; SHAP feature importance	
6	(K Praveen, 2022)	Sone command area in Bihar, India	Landsat-8, ASTER, Cartosat-1, SRTM; climate (temperature, rainfall, ET); DEM; soil properties; NDVI; canal data (Google Earth)	GIS (ArcMap, Google Earth, CROPWAT); PCA; weighted overlay; interpolation; correlation analysis; AI, PET, ETc, NDVI, crop coefficient calculations	Irrigation potential assessment; gap analysis (planned vs actual); agricultural suitability mapping; multi-factor evaluation (slope, rainfall, soil, AI, vegetation)	NA	Irrigation potential ~654,000 ha; minimal gap (~744 ha); ~75% moderate potential; central zone highest; low AI & gentle slope favorable; rice dominant crop (~75%)
7	Yousuf et al. (2026)	Rupnagar district, Lower Shivaliks, Northwest India	IMD rainfall data (2001–2021), FAO soil map, ALOS PALSAR DEM (12.5 m), ESRI LULC imagery (10 m), GIS datasets	GIS-based RUSLE model integrated with Remote Sensing and watershed prioritization	Soil erosion assessment and watershed prioritization	Spatial validation using erosion severity mapping and watershed ranking analysis	Average annual soil loss was 15.43 t ha ⁻¹ year ⁻¹ ; WS-2 showed highest erosion risk and was prioritized for soil and water conservation measures
8	(Ray, 2025)	Jamsholaghat watershed, Subarnarekha Basin, spanning West Bengal and Odisha provinces, India	Landsat 8 (Bhuvan); DEM (12.5 m, Alaska); rainfall (CHRS, IMD); lithology (GSI); soil maps; field observations	AHP–TOPSIS; 12 thematic layers; pairwise weighting (CR<0.1); PIS/NIS ranking; weighted overlay; multicollinearity (VIF); sensitivity analysis; GIS (ArcGIS), SPSS	Groundwater potential mapping; recharge zone identification; multicollinearity check; geospatial analysis (lithology, geomorphology, climate); water resource management	ROC-AUC (0.85); well yield validation (33 points); high accuracy (only 3 mismatches)	GPZ: high (40%), medium (52%), low (8%); eastern zone most suitable; key factors (lithology, geomorphology, slope, rainfall, LULC, lineament density); lithology highest weight (24%); high influence of distance from river & lithology; improved accuracy (AUC=0.85)
9	(Onglassynov et al., 2025)	Zhambyl Region in Southern Kazakhstan	Landsat-8/9 (30 m, Aug 2024, 13 scenes); SRTM DEM (30 m); climate data (WorldClim, CHIRPS); soil data (global DB + 84	AHP; MCDA (WLC); NDVI; fuzzy MCE (gamma); Monte Carlo uncertainty (300 runs, ±15%); Jenks classification; GIS; criteria (aquifer depth,	MAR site selection; groundwater stress mitigation; irrigation support; aquifer recharge enhancement; land restoration (~37,500 ha); MAR	CR<0.1; field validation (11 sites); lab analysis (ISO/IEC 17025); Monte Carlo sensitivity (300 runs); fuzzy	High MAR suitability (~19%, 27,060 km ²); shallow aquifers (5–20 m, low TDS); high infiltration (20–90 L/s); key zones (Kyrgyz Alatau piedmont, Talas-Assa); good water quality (<685 mg/L); major aquifers (alluvial, Neogene,

			samples); groundwater data (25 samples – ions, metals, TDS, pH); hydrogeological atlas; Sentinel-2 LULC (10 m, CNN); field investigations (11 sites)	mineralization, rainfall, slope, soil, LULC, NDVI, lineament, drainage)	structures (infiltration, check dams, injection wells)	comparison (MAE≈0.41, r≈0.47); climate data calibration (6 stations)	karst); land restoration (~37,500 ha); uncertainty in drainage/lineament zones; MAR solutions (infiltration, check dams, injection wells); groundwater underutilized vs surface water dependence
10	(Bah Ntutuwouo et al., 2024)	andjock, located in the Haute Sanaga division in the central region of Cameroon	SRTM DEM (1 arc-sec); satellite imagery (LULC); rainfall data (Nsimalen station); soil maps (texture, type); geological data (CGWB); location maps (Survey Cameroon)	AHP-GIS; pairwise weighting (1–9 scale); CR check; GWPI; GIS (ArcGIS, ENVI); criteria (drainage, lineament, slope, LULC, rainfall, soil, geology)	Groundwater potential mapping; water table evaluation; high potential zone identification; resource management; decision support	CR≤0.1; AHP consistency check; eigenvalue-based validation	GPZ: very high (31.35%), high (15.15%), medium (8.81%), low (43.12%), very low (1.57%); eastern zone most favorable; key factors (low slope, high rainfall, drainage, sandy soils); rainfall (1425–1550 mm); high lineament density → high recharge
11	(Firoz et al., 2026)	Rajshahi City Corporation (RCC), northwestern Bangladesh, on the northern banks of the Ganges River	Landsat multi-temporal (1990–2024, 30 m); groundwater level (6 stations); groundwater quality (14 zones); rainfall (World Bank, 1990–2024); river discharge (GEOGLOWS)	MLC classification; water indices (NDWI, MNDWI, MBWI, AWEI); IDW interpolation (GWL); Pearson correlation; lab analysis (titration, UV, AAS)	LULC & water dynamics analysis (1990–2024); groundwater depletion assessment; water quality analysis; urban planning & water management	Confusion matrix (200 points); accuracy metrics (UA, PA, OA, Kappa); cross-validation (indices vs classification); OA >85%	Built-up ↑543.56%; vegetation ↓78.29%; water bodies ↓79.34%; GWL decline (pre: 6.38 m, post: 4.25 m); strong correlation (r≈0.96–1.00); EC & TDS increased
12	(Kabo-Bah et al., 2025)	The White Volta Basin is located in northern Ghana, a transboundary watershed shared with Burkina	GCM precipitation (15 models, SSP scenarios); ERA5 reanalysis (1981–2020); station data (3 sites); DEM (30 m); geospatial factors (slope, drainage, soil);	AHP-GIS; multi-criteria (elevation, slope, drainage, soil); flood susceptibility mapping (near/mid/long-term); CMhyd bias correction (quantile mapping)	Flood vulnerability assessment; climate change scenarios (SSP); flood susceptibility mapping; disaster risk reduction; land-use planning	ROC-AUC (ArcSDM); model metrics (R ² , NSE, Pbias, RMSE)	Flood zones: very high (12.09%), high (22.56%), moderate (24.38%); future risk reduction (SSP5-8.5); decreasing rainfall; AUC=0.795; improved bias correction (R ² up to 1); high-risk areas in NE & south

		Faso, Togo, and Côte d'Ivoire	downscaled climate data				
13	(Thakural et al., 2025)	The Bina River basin is located in Madhya Pradesh, India	Rainfall (IMD, 2001–2020, 0.25°); soil map (FAO, 1:50,000); SRTM DEM (30 m); LULC (Sentinel-2, 10 m, ESRI)	USLE (R, K, LS, C, P); GIS (ArcGIS); rainfall erosivity; soil erodibility; topographic factor (DEM); LULC-based C & P factors	Soil erosion assessment; soil loss estimation; hotspot identification; land management planning; conservation strategies; water quality protection	NOT	Soil loss: 144,888 t/yr (avg 2.26 t/ha/yr); range (0–340 t/ha/yr); slight erosion dominant (82%); moderate–high (~17%); severe <1%; key drivers (low vegetation, slope); R (691–789), K (0.21–0.23), LS (0.005–37)
14	(Sharma & Singh, 2025)	The Mandi district is located in northern Himachal Pradesh, India.	DEM (USGS); satellite data (Bhukosh – geology, geomorphology, lithology); soil data (NBSS); rainfall (IMD); LULC (Landsat); thematic layers (soil, slope, geology, drainage, rainfall, lineament, geomorphology)	AHP; GIS (ArcGIS Pro); weighted overlay (WOI); pairwise comparison (Saaty scale); CR validation	Groundwater recharge mapping; potential zone identification; resource planning; water management; sustainable development	ROC-AUC (0.805); well data validation (13 points); high accuracy	GPZ: very good (13%), good (26%), moderate (40%), poor (21%); moderate zones dominant; wells mostly in good–moderate zones; accuracy (AUC=0.805); CR=0.075 (reliable)
15	(Wagoneka et al., 2025)	Upper Manyame sub-catchment (UMSC) in Zimbabwe	Landsat (1980–2020, 30 m); SRTM DEM (30 m); soil (HWSD); rainfall (CHIRPS); geology (GS Zimbabwe); thematic layers (geology, LD, rainfall, soil, slope, distance to river, TWI, elevation, LULC)	MLC classification; AHP (pairwise, Saaty); WLC; fuzzy logic; Markov chain (LULC projection 2030); GIS (ILWIS, QGIS)	Groundwater potential modelling; LULC impact assessment; recharge zone analysis; sustainable groundwater management; decision support	Correlation analysis (713 boreholes); R ² =0.7152	LULC change: settlements ↑961%, bare ↑242%, cultivation ↑102%, forest ↓69%, grass ↓49%; accuracy (~93%, kappa 0.91); GWRZ: moderate (60%), high (21%), low (18%); borehole validation (majority moderate); future LULC change (settlements ↑, forest ↓)
16	(Rajasekhar et al., 2022)	The north-western part of Anantapur district in southern	Landsat-8; Cartosat DEM; SOI topo maps; soil data (Anantapur); rainfall (1998–2018); lineament data; thematic layers	AHP; GIS (ArcGIS); weighted overlay (WOA); pairwise comparison (Saaty); CR<0.1 validation	Groundwater potential mapping; GWPZ identification; artificial recharge planning; drought management;	ROC-AUC (0.78); well data validation; moderate–high accuracy	GPZ: very good (2.45%), good (12.76%), moderate (63.47%), poor (15.99%), very poor (5.32%); moderate dominant; CR=0.09 (consistent); key weights (LULC, DD, rainfall highest); rainfall (187–

		Andhra Pradesh, India	(geomorphology, LD, DD, geology, LULC, soil, slope, rainfall)		sustainable groundwater use		536 mm); slope & LD influence recharge
17	(Majumdar et al., 2022)	Arizona, USA; Basin & Range aquifer (south/west) and Colorado Plateau aquifers (north/east); includes AMAs & INAs	SSEBop ET; PRISM precipitation (4.1 km); CDL (30 m, 2008–2020); sediment thickness (USGS); InSAR subsidence; groundwater withdrawal data (ADWR, 2002–2020)	Random Forest (RF); multivariate regression; predictors (AGRI, URBAN, SW, CC, ET, P, stress, AD, WD); data split (temporal, spatial, spatio-temporal); GEE processing	Groundwater withdrawal estimation (2 km); subsidence analysis; sustainable groundwater management; data-scarce region support	R ² , RMSE, MAE; NRMSE, NMAE; model performance (R ² ≈0.9 train, 0.7 test); validation with InSAR subsidence	Model performance (R ² ≈0.9 train, 0.7 test); key drivers (WD, AGRI, URBAN, SW); groundwater–subsidence linkage; confined aquifer loss (~10%); good generalization
18	(Maqsoom et al., 2021)	The study was conducted in Chitral district, located in the northern region of Pakistan	Nitrate (29 wells); population (GPWv4); vadose zone, aquifer, soil data (PCRWR); rainfall; hydraulic conductivity; ASTER DEM; FAO land use	Modified DRASTIC (DRASTICA); GIS (ArcGIS); 8 parameters (D, R, A, S, T, I, C + anthropogenic); RBF & kriging interpolation; rating-weighting; sensitivity analysis	Groundwater pollution susceptibility mapping; anthropogenic impact assessment; decision support for groundwater protection; planning under CPEC development	Pearson correlation; nitrate vs DI & MDI; improved performance (r=0.78 vs -0.53); model validation	Higher vulnerability in modified model (+17% high zones); high-risk areas dominant; spatial variation (west/upper high, central moderate); key factor (hydraulic conductivity); urban nitrate impact
19	(Lavanya & Muthukumar, 2024)	Dindigul district in Tamil Nadu, India	14 layers: lithology, geomorphology, lineament density; subsurface (topsoil, fractured, weathered); LULC; soil; rainfall; slope, TWI, roughness, curvature; drainage density; groundwater level	AHP; pairwise comparison; weighted overlay; GIS (ArcGIS); spatial analyst tools; thematic layer integration	Groundwater potential mapping; thematic layer preparation; AHP weighting; weighted overlay; validation using water level data; support for sustainable management	Well validation (38 wells, 2017–2022); water level classification; moderate agreement (~60.53%); field validation	GPZ distribution (very high–very low); moderate zones dominant; high zones in fractured/weathered areas; low zones in hilly terrain; validation agreement (~60.53%)
20	(Balasubramaniyan et al., 2025)	Natham Taluk, Dindigul	10 layers: lithology; LULC; lineament, drainage density;	AHP; pairwise comparison; weighted overlay (ArcGIS); RS-	GWPZ mapping in hard rock terrain; sustainable groundwater	ROC-AUC (0.83); borewell validation (51 wells);	GPZ classes (very good–very low); good zones dominant (~39.7%); high zones in fractured northern

		district, Tamil Nadu, India.	geomorphology; soil; DEM (slope, TWI, curvature); rainfall; borewell data (51 wells)	GIS integration; ROC-AUC; borewell validation	development; recharge site identification; support for artificial recharge planning	classification-based validation; reliable model accuracy	areas; AUC=0.83 indicates strong model accuracy
21	(M. Hossain et al., 2024)	West Bengal, India, covering 19 major districts	Groundwater quality (479 wells–2009, 734 wells–2021; 13 parameters); Landsat 7 & 8 (30 m); GSI geology maps	MLC (LULC); EBK interpolation; RSM–LULC analysis; ANOVA & Friedman tests; ERI & WPI indices; GIS (ArcGIS)	LULC–groundwater quality analysis; health & ecological risk assessment; decadal change (2009–2021); GIS–RSM integration for management	ANOVA (p=0.0002); F-value (5.83); R ² =0.87; adjusted R ² =0.72; diagnostic plots (~97.5% agreement); model validation	Water quality decline (↓excellent, ↑polluted); LULC correlation (built-up/agriculture ↑WPI, forest/water ↓WPI); LULC changes; reduced ecological risk; significant statistical differences
22	(Shandu & Atif, 2023)	Ison Mandela Bay (NMB) District, South Africa.	Precipitation (TerraClimate); LULC (Sentinel-2, SVM); lineament density; DEM (slope, TWI, drainage); lithology; soil; boreholes (1371 samples)	AHP (pairwise, CR=0.025); Random Forest (200 trees); weighted overlay; GIS (ArcGIS); ML–GIS integration	GWPZ mapping; water scarcity management; groundwater exploration planning; support for sustainable resource development	ROC-AUC; RF (0.81) > AHP (0.79); good model accuracy; reliable prediction	GPZ classes (high dominant ~60%); RF better than AHP (AUC 0.81>0.79); high zones in southern region; flat slopes favor infiltration; water scarcity despite good potential
23	(Ajayi et al., 2022)	Bosso Local Government Area (LGA), Niger State, North-Central Nigeria.	Sentinel-2A (10–60 m); SRTM DEM (30 m); geology & hydrogeology vectors; VES hydrogeophysical data	AHP (pairwise); MLC classification; MCDA; weighted overlay (ArcGIS); RS-GIS integration	GWPZ mapping; cost-effective alternative to geophysical surveys; groundwater exploration planning; support for water resource management	VES validation; Pearson correlation (r=0.681); strong agreement; field-based validation	GPZ classes (moderate dominant ~85%); geology key factor (56%); high zones in NE; low zones in SW; VES validation (r=0.68)
24	(Hoogeweg et al., 2020)	The CILSS (Permanent Interstate Committee for Drought Control in the Sahel) region of West Africa	GlobCover LULC (300 m); SPAM crop data (10 km); SoilGrid (250 m); HydroSHEDS surface water; groundwater depth data	GIS (ArcGIS 10.5); weighted overlay; land use classification (GlobCover); spatial combine analysis (crop + soil vulnerability)	Acetochlor risk mapping; crop–soil vulnerability analysis; groundwater/surface water contamination assessment; support for management practices	No formal validation; dataset comparison; LULC overlap analysis (24.7–85%); uncertainty assessment	Large vulnerable soils (~462 Mha) but low risk overlap; limited acetochlor use area (~2.2 Mha); minimal groundwater/surface water risk; small fraction of agricultural land affected

25	(Ayadi et al., 2025)	The Majerda Transboundary Basin, located in North Africa, spanning northern Tunisia and northeastern Algeria	Sentinel-2 (10 m LULC); SRTM DEM (30 m: slope, drainage, lineament); rainfall (CRU TS); lithology & geomorphology; soil (FAO)	AHP vs Geo-AI comparison; GWPZ mapping; groundwater recharge assessment; support for sustainable management	AHP vs Geo-AI comparison; GWPZ mapping; groundwater recharge assessment; support for sustainable management	Field validation (hydrogeological data); well/spring discharge comparison; no standard metrics; classification accuracy assessment	Geo-AI (92%) > AHP (85%); moderate zones dominant (~66%); similar spatial patterns; rainfall, slope & lithology key factors; strong field validation (high discharge zones)
26	(Ruttoh et al., 2022)	Kibwezi watershed located in Semi-Arid Eastern Kenya, Makueni County, in the lower part of the River Athi basin	Landsat (1999–2019, 30 m); SRTM DEM (30 m); field GPS data (547 points)	RS-GIS; SWAT model; ISODATA classification; minimum-distance classifier; post-classification processing	LULC mapping & change detection (1999–2019); watershed delineation (SWAT); conversion analysis; support for watershed management	Accuracy assessment; Kappa (0.85); overall accuracy (87.4%); user & producer accuracy; field validation (547 points)	LULC change (1999–2019); major increase (shrub grassland, urban, crops); major decrease (open/closed shrubland); cropland & woodland dominant; strong urban expansion
27	(Oladotun, 2022)	Opa watershed located in Southwestern Nigeria (Osun State)	NIGSAT (32 m); SRTM DEM (30 m); soil (HSG); rainfall (77 mm event)	SCS-CN model; MLC classification (IDRISI); GIS (ArcGIS); CN grid generation; runoff estimation	Runoff estimation (SCS-CN); flood risk assessment; watershed flood prediction; support for disaster management	NA	Runoff variation by land cover; high CN in urban areas (high runoff); low runoff in vegetated zones; urbanization increases flood risk; effective SCS-CN modeling
28	(Feng et al., 2025)	The Bakhtegan watershed is located in southwestern Iran	Landsat TM-ETM+; DEM (30 m); geology (GSI); landslide inventory (235 points); rainfall & temperature (IMO); seismic data (IIEES)	CNN (deep learning); RS-GIS (ArcGIS); Python (TensorFlow, Keras); normalization; model comparison (MLP, RF, SVM, DT, AdaBoost)	Landslide susceptibility mapping; CNN-based modeling; high-precision prediction; analysis of geo-environmental factors	Confusion matrix; MAE, MSE, RMSE; 70–30 train-test split; field validation; comparative analysis (CNN vs MLP, LR, RF, DT, AdaBoost, SVM)	CNN accuracy 95.76%, precision 95.11%, MAE 0.1186, MSE 0.1879, RMSE 0.1863; high landslide susceptibility in northern & northeastern regions; risk zones: very high (30%), high (30%), moderate (15%), low (25%); 235 landslide & 235 non-landslide samples; CNN outperformed MLP

							(81.35%), RF (70.20%), LR (65.70%), DT (79.85%), SVM (80.80%)
29	(Modaresi Rad et al., 2024)	The study covers the Continental United States (CONUS)	ADCP field data (>200,000 measurements: depth, width, velocity, discharge); NWM v2.1 discharge & flow percentiles; NHGF network & EPA StreamCat (58 predictors); climate data (TerraClimate, NLDAS, GLDAS, USGS 3DEP); soil & vegetation (POLARIS, LAI, MODIS); NWIS historical discharge records	ML ensemble modeling; SHAP feature importance & PCA for reduction; 40 models tested (NN, tree, SVM); top models (XGB, RF, HGB, LGBM, ElasticNet, MLP, BayesianRidge, ARD, KNN, Bagging); meta-learner ensemble; 15 key predictors selected (elbow method)	ML-based estimation of river channel geometry (bankfull width & depth); improve predictions for gauged & ungauged basins; support flood modeling, hydrological analysis & river management	R ² (log-transformed) & RMSE; 5-fold cross-validation (3 repeats); train-validation-test split (70–10–20); comparative evaluation with regional, global & ML models	Model performance: bankfull depth (R ² =0.80), width (R ² =0.76), in-channel depth (R ² =0.77), width (R ² =0.66); best in plains & some mountainous regions, lowest in humid plains (R ² ≈0.53); key predictors: discharge, flow length, TWI, AET, elevation, slope; thresholds: TWI≈810 & AET≈65; ML ensemble outperformed regional & global models
30	(Yadav & Dey, 2025)	The Shilabati River Basin (SRB) located in West Bengal, India	Landsat 9 (2023, 30 m) LULC; SRTM DEM (30 m) for elevation, slope & drainage; rainfall (NASA POWER, 2010–2020); soil data (FAO/UNESCO); geomorphology (GSI); field samples (72 sediment + monsoon water samples, 2023)	SCS-CN model with RS & GIS; integration of HSG, LULC, slope & hydro-climatic factors; Thiessen polygon rainfall interpolation; weighted curve number approach; AMC classification (I, II, III)	Runoff estimation using SCS-CN; simulate surface runoff & discharge with RS-GIS; assess runoff under AMC conditions; support water resource management & hydraulic planning (Shilabati Basin)	Correlation analysis (r=0.97) between rainfall & runoff; strong positive relationship validating SCS-CN model reliability	HSG: A (71%), B (18.2%), C (10.8%); CN: avg 80.12 (AMC-I:64.12, AMC-III:89.98); runoff depth ~1920–2184 mm (avg 2052 mm), discharge up to 154.7 m ³ /s; LULC dominated by plantation & forest; strong rainfall-runoff correlation (r=0.97); HI=0.487 (mature basin); gentle slopes dominate; high TDS & contamination in low-lying zones
31	(Anand et al., 2025)	Delhi, a small region of the Indo-Gangetic plain of India	SRTM DEM (30 m) with slope, aspect, TWI & SPI; Landsat 8 (NDVI, LST); geomorphology (GSI); soil data (FAO);	Ensemble ML with GIS; models: RF, AdaBoost, NN, DT, kNN, XGBoost; 11 conditioning factors (elevation, slope, soil,	ML-based groundwater potential mapping; compare six ensemble models with GIS; identify priority zones for sustainable water	AUC, accuracy, F1, precision, recall, MCC; spatial cross-validation; stratified sampling (70–30 split)	RF best (AUC=0.910, CA=0.778); AdaBoost strong (AUC=0.897, highest MCC=0.672); other models lower (GB=0.885, kNN=0.822, NN=0.725, DT=0.659); key factors: geomorphology, elevation,

			rainfall (IMD, kriging); LULC (Sentinel-2, 10 m); groundwater points (136 sites, WRIS)	geomorphology, aspect, rainfall, LULC, SPI, TWI, LST); min-max normalization	management in urban areas		rainfall; high GWP in south, moderate central/north, low NE; RF most reliable, AdaBoost robust for imbalance
32	(Goodrich et al., 2020)	The Cienega Creek watershed (CCW) and Empire Ranch located in southeastern Arizona	Landsat imagery (1992–2016, 30 m); NRI point data (vegetation parameters); DEM (NED ~10 m & 1 m); LiDAR (pond dimensions); aerial imagery; field vegetation data (transects, 2005–2009)	AGWA for watershed delineation; RHEM for runoff & sediment modeling; RaBET (ArcGIS) for woody canopy mapping; NMDS & clustering for ecological grouping	Evaluate CEAP grazing land practices (brush removal, burns, stock ponds); assess impacts on hydrology & soil loss; monitor vegetation change using remote sensing	Relative change analysis (no direct calibration data); RaBET validation with field plots; SATVI–foliar cover regression ($R^2=0.34$)	Sediment: +11% (1992), +33% (2003–06), –1.7% (2011–14); runoff minimal (–1.15% to 3.34%); vegetation improved (nonshrub 20%→44%); brush removal reduced sediment (6–19%); fire less effective; stock ponds reduced sediment ~65% ($\approx 2.9\times$ more effective); monsoon rainfall $\uparrow 18\%$; RS+models effective for large-scale assessment
33	(Takele et al., 2025)	The Ziway Lake Watershed (ZLW) located in the central Main Ethiopian Rift (MER)	Landsat 8 (LULC & NDVI); DEM (12.5 m); soil (HWSD/FAO); geology (Ethiopia); climate (1982–2016, 14 stations + NCEP); river discharge (Katar & Meki); field data (80 water points)	SWAT model (ET estimation); AHP-MCDA weighting; GIS overlay (WLC); RS for NDVI & lineament extraction; 10 factors (rainfall, lithology, elevation, LD, slope, NDVI, LULC, soil, ET, drainage)	Map groundwater recharge zones; support sustainable water management & policy; identify sites for rainwater harvesting & MAR; support afforestation & climate adaptation (Ziway Lake)	ROC-AUC ≈ 0.80 (80 water points); SWAT validation: Katar ($R^2=0.86$, NSE=0.84, PBIAS=3.2%), Meki ($R^2=0.79$, NSE=0.78, PBIAS=5.9%)	Recharge zones: very low 18.05%, low 23.61%, moderate 21.89%, high 19.64%, very high 16.81%; >58% moderate–very high potential; high zones in gentle slopes & permeable lithology; key factors: rainfall (26%), lithology (21.5%), elevation (14%); ET ~689.9 mm/yr, rainfall 654–1140 mm; AHP CR=0.031
34	(“Integration of Remote Sensing, GIS, and SCS-CN Model for Runoff Volume Estimation in Al-Deir Valley Basin, Iraqi Jazira Desert,” 2025)	Al-Deir Valley Basin located in the Iraqi Jazira Desert	Landsat 8 (2025, 30 m); soil (HWSD); rainfall (1990–2024, IDW interpolation); geology (Iraq map); administrative boundaries; field GPS data for classification	SCS-CN model; RS-GIS with MLC classification (ArcMap 10.8); CN mapping using LULC & HSG; IDW rainfall interpolation; sensitivity analysis ($\pm 5\%$, $\pm 10\%$)	Assess water harvesting potential using SCS-CN; estimate runoff in ungauged basin; GIS-RS basin characterization; evaluate suitability for water harvesting (Al-Deir Valley)	LULC accuracy 85% (Kappa=0.80); sensitivity analysis ($\pm 5\%$, $\pm 10\%$ CN); runoff variation ± 11 –26%; no direct field validation	Barren land 57%, poor vegetation 40.3%; soils: Group C 66.6%, B 33.3%; CN 77–90 (dominant 90); runoff depth 81–115 mm, volume 1.14–4.96 MCM; high water harvesting potential (~1000 ha irrigation); high zones in central & north; model reliable via sensitivity analysis
35	(Asagadunga et al., 2025)	Sunyani Municipality, located in	Landsat 7 (2003) & Landsat 8 (2013, 2023, 30 m); shapefiles	RS-GIS preprocessing (correction, stacking, extraction); MLC	Assess status of water bodies & wetlands; evaluate effectiveness of	Confusion matrix (200 samples/year); accuracy: 88%	Water decline: 7.95%→2.39%; vegetation loss ~3662 ha; built-up expansion 35.06%→64.63%; major

		the Bono Region of Ghana	(Ghana admin, DIVA-GIS, Google Earth); qualitative interviews (5 institutions)	supervised classification (ArcMap); post-classification change detection; NVIVO qualitative analysis	management systems for protection (Sunyani)	(2003), 86% (2013), 88.5% (2023); Kappa: 0.84, 0.78, 0.77	conversion: vegetation→built-up (~4219 ha); weak management & poor stakeholder involvement; high classification accuracy (vegetation 99%, water 95%)
36	(Rashid et al., 2025)	District Rahim Yar Khan, Pakistan	Landsat 5, 7, 8 (USGS); census data (PBS); multi-temporal datasets (2000, 2008, 2013, 2018, 2022)	RS-GIS techniques; spectral indices (NDVI, NDBI, NDWI); MLC supervised classification (ArcGIS); change detection & accuracy assessment	LULC change analysis; assess impacts of population growth, urbanization & agriculture; support sustainable planning & future prediction	Confusion matrix; metrics: OA, PA, UA, Kappa; accuracy >85% (acceptable standard)	Built-up ↑ (42→113 km ²); vegetation fluctuated (max 6485 km ² in 2008, min 5440 km ² in 2018); water bodies variable (159–187 km ²); barren land ↓ (6719→5468 km ²); fallow land ↑ (95→1415 km ²); strong impact of urbanization & agriculture
37	(Xu et al., 2025)	Loktak Lake located in Bishnupur district of Manipur, India, within the Indo-Burma Biodiversity Hotspot in northeast India	Landsat MSS (1977) & IRS LISS III (2015); SOI toposheets (1:50,000); GPS field data for ground truth	RS-GIS techniques; ERDAS Imagine & ArcGIS; MLC supervised classification; preprocessing (georeferencing, mosaicking, subsetting, resampling)	LULC change analysis (1977–2015); assess impacts on Loktak wetland ecosystem; support sustainable water resource & land use management	Confusion matrix (stratified sampling, 50 points/class); Kappa analysis; overall accuracy 86%	Open water ↑ (+26.89 km ²); agriculture ↑ (+25.33 km ²); settlements ↑ (+5.75 km ²); Phumdis thick ↓ (−8.59 km ²), thin ↓ (−49.38 km ²); driven by Ithai Barrage, population growth & resource demand
38	(Md. Z. Hossain et al., 2024)	e Barind Tract (BT) in the northwestern region of Bangladesh	SRTM DEM (30 m); Landsat 8 (LULC); rainfall (BMD); geology & soil (BARC); time period 2018–2022	AHP-GIS (ArcGIS 10.5); 7 factors (rainfall, soil, geology, slope, lineament, LULC, drainage); IDW (rainfall); MLC (LULC); DEM-derived slope & drainage; weighted overlay	Groundwater recharge potential mapping (Barind Tract); delineation using AHP-GIS; supports sustainable water management & policy planning	AHP consistency check (CR=0.0904<0.1); validation via FAO guidelines & literature comparison; no field validation	Recharge zones: moderate (47.68%) dominant; good (37.12%); poor (9.23%); very good (5.97%); recharge ≈2554×10 ⁶ m ³ /yr (22.7% rainfall); geology highest influence (33.57%)
39	(Dasari et al., 2025)	Salebhata catchment (Mahanadi basin,	Sentinel-2 (10 m LULC); SRTM DEM (30 m); soil (OpenLand & USDA,	Modified SCS-CN; AMC adjustments (I, II, III); slope-corrected CN; RS-GIS integration;	DSS for runoff estimation; supports historical & future (CMIP6) simulation;	R ² validation: Salebhata (0.82), Venkatapur (0.78); strong agreement	Strong model performance (R ² : 0.82, 0.78); captures monsoon peaks & bimodal runoff; scalable across basin sizes; effective for

		Odisha–Chhattisgarh ; 4588.9 km²; humid, 1350–1500 mm rainfall); Venkatapur sub-watershed (Krishna basin, Karnataka; 685 km²; semi-arid, 650–750 mm rainfall)	250 m); CHIRPS precipitation (5 km); CMIP6 climate (25 km); observed runoff (CWC)	Google Earth Engine implementation	flood forecasting; climate-resilient water resource planning	between simulated and observed runoff	flood forecasting & water management
40	(Heidarian et al., 2025)	The Marvdasht Plain located in Fars Province, Iran	Sentinel-1 SAR (432 scenes, 2015–2022); Landsat indices; SRTM DEM (30 m); hydroclimate (GRACE TWSA, precipitation, temp, humidity, PET); biophysical (NDVI, EVI, LAI, FPAR, NDWI, GPP); soil (OpenLand); 54 boreholes	SBAS-InSAR (LiCSBAS); deep learning (LSTM, BiLSTM, CNN-LSTM, Transformer, ConvTransformer, Informer); standardized scaling; multi-band feature extraction; tiled raster processing	Predict groundwater levels & depletion (Marvdasht Plain); compare deep learning vs transformer models; identify drivers; support early warning & heritage protection	R², RMSE, MAE, MAPE, r; Taylor diagram; regression & scatter plots; spatial validation; 70/30 train-test split	ConvTransformer best (R²~0.83; low errors); strong groundwater decline (10–25 m); subsidence >180 mm/yr linked to depletion; key drivers: InSAR velocity, NDVI, GPP
41	(Poudel et al., 2024)	Doramba Rural Municipality , Ramechhap district, in the mountain	SRTM DEM (30 m); remote sensing data; LULC; soil & geology maps; field survey data; ICIMOD sources	AHP (Saaty); GIS-RS integration; 11 factors (drainage, slope, rainfall, lineament, LULC, soil, geology, curvature, roughness, TWI, TPI)	Groundwater potential zone mapping; assess spatial distribution; support sustainable water management in mountainous regions	Field validation using 56 springs; prediction accuracy 70.7%	Moderate (46.61 km²) dominant; high & low zones significant; very high limited; validation accuracy 70.7%; supports groundwater management

		region of Nepal					
42	(Ishola et al., 2023)	The University of Ilorin (UNILORIN) landmass in Ilorin South Local Government Area of Kwara State, North-central Nigeria	Landsat 8 OLI (2019); SRTM DEM (30 m); aeromagnetic data; PERSIANN-CDR rainfall; soil (FDALR); borehole data & lithologs	AHP-GIS; aeromagnetic processing (RTE, FVD, SVD, AS-FFT); 7 factors (drainage, lineament, LULC, soil, rainfall, slope, geomorphology)	Groundwater potential zonation (UNILORIN, Ilorin South); map spatial distribution; support sustainable groundwater management	ROC-AUC validation using borehole data	Moderate (60.6%) dominant; low (33.5%); high limited (5.9%); AUC=0.73 (good prediction); moderate–high potential overall; aeromagnetic integration effective
43	(Shekar et al., 2025)	The Akeru watershed in Telangana state, India	SRTM DEM (30 m); geomorphology & lineament (GSI); terrain derivatives (slope, TWI, TPI, drainage, curvature, river distance); ESRI LULC (10 m); rainfall (CRU); 30 wells	AHP-GIS; 10 factors (drainage, rainfall, TWI, curvature, elevation, geomorphology, TPI, river distance, LULC, slope); pairwise matrix; weighted overlay	GWPZ mapping & artificial recharge site identification (Akeru watershed); supports site selection for recharge structures (ponds, check dams)	ROC-AUC validation (ArcGIS ArcSDM toolbox)	Moderate (74.6%) dominant; high (19.5%); low (5.9%); 176 recharge sites (majority moderate); AUC=0.81 (high accuracy); key factors: rainfall, drainage, river distance, geomorphology
44	(Waindeshkar et al., 2025)	per Bhima River Basin, including parts of Bhor Taluka in Pune district and Khandala Taluka in Satara district, Maharashtra, India.	Landsat 8 (2015, 2020, 2024; 30 m); GEE platform; cloud-free scenes (<10%); UTM Zone 44N	Supervised classification; GEE processing; 5 classes (water, built-up, barren, forest, agriculture); post-classification change detection; ArcGIS visualization	LULC change analysis & groundwater recharge (Deccan basalt, Satara); assess impacts on subsurface water; support sustainable management & climate resilience	Confusion matrix; Kappa coefficient (GEE-based validation)	Built-up ↑ (+7.99%); agriculture ↑ (+4.99%); forest & barren ↓ (−2.38% each); water slight ↓; accuracy improved (85→89%, Kappa 0.768→0.867); urbanization major driver

45	(Ragonese & Massarelli, 2026))	Apulia, situated in the southeastern extremity of the Italian peninsula	Water samples (2018–2024; ~1000 observations); Corine LULC; DEM; slope (river offset lines)	UHPLC-MS/MS (LOQ 0.025 µg/L); hybrid ML (RF, GB, KNN); global & segment-wise models	Predict glyphosate/AMPA; map hotspots; spatial river profiling	R ² : 0.68 (global), 0.75 (local); RF baseline R ² : 0.677	AMPA > glyphosate (9.27 µg/L); high persistence (240 days); seasonal peaks (Q2 glyphosate, Q4 AMPA); RF best model; cost-effective monitoring
46	(Ragonese & Massarelli, 2026)	Integrated Watershed Management Project (IWMP) watershed in Sagar district, Shahgarh block, Madhya Pradesh, India	LISS-4 (5.8 m) + Cartosat-1 (2.5 m); field survey; POI (smartphone); watershed & drainage data	GIS; visual LULC; NDVI; change matrix; union analysis; Srishti & Drishti apps	IWMP monitoring; transparency assessment; geospatial & mobile-based tracking; LULC change analysis	Field validation (Drishti app); ground truthing; no statistical metrics	Cropland ↑275.89 ha; water bodies ↑60.73 ha; scrubland ↓361.75 ha; IWMP structures; positive agri & groundwater impact
47	(Beden et al., 2023)	The Kızılırmak Delta located in the Black Sea Region of Turkey	ESRI LULC (2022); Landsat 8; precipitation (MGI, 1960–2022); soil; geology (1:50,000); SRTM DEM (30 m)	GIS; RS; AHP; weighted overlay (GPZ mapping)	Delineate GPZ; identify recharge zones; support groundwater management	AHP consistency ratio (CR = 3% < 10%); no field/statistical validation	Very high 38%; high 19%; moderate 39%; poor 4%; precipitation (40.9%) dominant factor
48	(Mengistu et al., 2022)	The Gilgel Gibe Catchment located in Eastern Ethiopia in the Omogenebir e basin of southeastern Ethiopia	Rainfall (1988–2018, SWAT-IDW); SRTM DEM (30 m); LULC (30 m); HWSD soil; geology; lineament; satellite proxy data	GIS; RS; AHP (10 factors); weighted overlay (PARZ mapping)	Map aquifer recharge zones; support groundwater management; address water scarcity	Field validation (inventory wells); AHP CR = 0.092 (<10%)	VH 29%; H 25%; M 28%; L 13%; VL 5%; lithology (20.2%) dominant; wells: 57% VH, 32% H

49	(Demelash et al., 2025)	e Nashe watershed located in the Fincha'a River sub-basin, Upper Blue Nile Basin, Western Ethiopia	Slope (SRTM DEM); soil (ISRIC, 250 m); LULC (Sentinel-2, 10 m); rivers & roads	AHP; GIS (ArcGIS 10.3); weighted overlay; IDRISI; ERDAS; ArcSWAT (8 criteria)	Irrigation suitability mapping; support agriculture; address water scarcity & food security	Spatial validation (overlay with existing irrigation plans); no statistical metrics	Highly 18.9%; moderate 68.8%; unsuitable 12.2%; slope (33%) dominant factor
50	(Megha D. Kokate, Ravi Kant Pareek, 2025)	The Nashik City region in India, specifically focusing on the Godavari River ecosystem	Topo maps (slope, aspect, hillshade, roughness); Landsat; flood data (1990–2024); hydrological; field data	GIS; RS; ML (KNN, RF, SVM, DT); AHP; unsupervised (K-means, SOM)	Flood risk mapping; runoff & discharge prediction; ML-based flood modeling; urban planning support	10-fold CV (KNN); accuracy ~88–89%; train 90.18%, test 89.70%; precision/recall/F1; confusion matrix	Moderate elevation dominant (50–60%); floodplains 15–20%; peak discharge ~7200 m³/s (2025); ML accuracy ~89%
51	(Korkmaz, 2026)	e Peri River Basin located in Eastern Türkiye, within the provinces of Elazığ and Tunceli	DEM (30 m, MTA); geology & soil; LULC; precipitation (WorldClim); drainage (DSI); HGM & MAF data	GIS (ArcGIS 10.5); AHP; narrow-valley detection; hydrology tools; 9 criteria	SHP site selection; GIS-AHP framework; sustainable water-energy planning	Spatial overlay (existing dams); AHP CR = 0.0952 (<10%)	Very high 3%; moderate 46%; 13 SHP sites identified; stream order (37%) dominant
52	(Korkmaz, 2026)	Dhaka Metropolitan Area (DMA), the capital city of Bangladesh,	Multitemporal Landsat imagery (1992, 2007, 2022; TM, ETM, OLI/TIRS) from USGS; same-season acquisition (<10% cloud); spectral bands: green (TM/ETM: B2, OLI: B3) and NIR (TM/ETM: B4, OLI: B5)	NDWI (green & NIR bands, -1 to +1) for water detection; GIS (ArcGIS 10.8) for spatial analysis & change detection; supervised LULC classification (4 classes) with transition matrix (Intersect)	Assess spatiotemporal waterbody changes (1992–2022, Dhaka); analyze urbanization & climate impacts; support sustainable urban water management	Accuracy assessment (UA, PA, OA, Kappa); OA: 88% (1992), 92% (2007), 90% (2022); Kappa: 0.84–0.88; NDWI + supervised validation	Waterbody ↓84.19→37.20 km² (1992–2022); loss 60.74 km²; built-up major driver; urban growth ~4%/yr

53	(Dhakal & Kattel, 2025)	Dailekh District, Karnali Province, Nepal	Soil samples (n=204, stratified); Google Earth Pro reference; parameters: N, P, K, OM, pH; field data	Ordinary Kriging (exp., circular); GIS (ArcMap 10.2); SPSS 27; QQ plot; 2nd-order polynomial trend analysis	Soil fertility mapping; spatial variability analysis; support nutrient management, crop suitability & precision farming	Cross-validation (min error); no AUC/R ² /ROC reported	N: 81% medium; P: 56% medium; K: 57% medium; OM: 65% low; pH: 49% acidic; CV highest in P (123.99%)
54	(Gulbet Tebege et al., 2025)	Libo Kemkem watershed, Northwestern Ethiopia	Sentinel-2A (10 m); ALOS-PALSAR DEM (12.5 m); meteorological data; soil (1:50k); geology (1:250k); field wells (n=11)	RS & GIS; AHP; weighted overlay (ArcGIS); 9 layers (slope, rainfall, drainage, lineament, soil, LULC, river distance, lithology, NDVI)	Delineate groundwater potential zones; support sustainable water management & extraction planning	Field validation (11 wells); accuracy 81.8%; ROC-AUC = 0.604	High potential ~40%; low-very low 27%; favorable: flat, high rainfall, lineaments; accuracy 81.8%
55	(Md. Z. Hossain et al., 2024)	West Bengal, India	Landsat 7 (2009) & Landsat 8 (2021, 30 m); groundwater data (479 & 734 wells); 13 parameters; geology (GSI); field sampling	MLC (LULC); EBK interpolation; WPI; RSM (CCD); ERI; GIS (ArcGIS 10.8); ANOVA & Friedman test	Assess LULC impacts on groundwater quality, health & ecological risks; support sustainable water management & policy	OA: 91% (2009), 92.7% (2021); Kappa: 0.89–0.91; R ² = 0.87; ANOVA p = 0.0002	Excellent ↓30.5→28%; polluted ↑44→45%; built-up ↑0.7%; cropland ↓2.4%; THI 0.84→0.75; ~21–24% health risk
56	(Luo et al., 2023)	two subtropical cities in China, Kunming (21,473 km ² , plateau monsoon, 102°10'–103°40'E, 24°23'–26°22'N); Fuzhou (11,968 km ² , marine monsoon, 118°08'–120°31'E,	Landsat TM (1995–2010) & OLI (2015, 2020, 30 m, GEE); NASADEM (30 m); socioeconomic data; admin boundaries	Random Forest (RF) & Support Vector Machine (SVM) for LULC classification; dynamic degree methods for land use change; DPSIR model with entropy weighting for ecological security assessment; gray relational analysis for correlation; GIS analysis using ArcGIS	Comparative analysis of ecological security response to LUCC in eastern and western subtropical China (Kunming vs. Fuzhou), assessing impacts of economic development and land use changes to support ecological security planning	Overall accuracy >88% and Kappa >0.84; validation using high-resolution Google Earth samples in ENVI 5.3; cross-check with GlobeLand30 for spatial and proportional consistency	LUCC (1995–2020): Dynamic degree higher in Kunming (1.05%) than Fuzhou (0.55%); Ecological Security Index increased (Kunming: 0.42→0.52, Fuzhou: 0.36→0.68); strong LUCC–ecological security correlation; woodland strongly correlated in both cities; water bodies highest correlation in Kunming (0.934); construction land highest in Fuzhou (0.887); RF outperformed SVM in classification accuracy

		25°15'– 26°39'N)					
57	(Naik & Sharma, 2021)	mbhar Salt Lake (SSL), located in the semi-arid climatic region of Rajasthan, India,	CORONA (1963), Landsat MSS (1972, 1981), Landsat 5 TM (1992, 2009), Landsat 8 OLI (2019, 30 m); Sentinel-2; field data (soil, water, bird census – 16 samples each); GPS (69 points); SOI toposheet (1954); Google Earth	Supervised Maximum Likelihood Classification (MLC) using ERDAS Imagine 2014; CA-Markov (LCM) model in TerrSet for future prediction (2029–2059); ArcGIS 10.5 for spatial analysis; dynamic degree, transition matrix, and correlation analysis	Assessment of long-term (1963–2059) LULC changes and drivers affecting Sambhar Salt Lake using geospatial modelling; integration of soil-water parameters and bird census data to support ecosystem restoration strategies	Classification accuracy ranged from 80.95%–87.50% (Kappa: 0.73–0.82); validation using 69 GPS points (48 for training, rest for testing); Google Earth verification; field validation of historical and birding sites	Wetland declined from 30.7% to 3.4% (1972–2019); saline soil increased (12.4%→21.7%); barren land (45.4%→49.6%); salt pan (7.4%→14%); settlement (0.1%→1.3%); bird population dropped from ~3 million to ~3,000; strong salinity–EC correlation ($r=0.99$); future: 40% wetland loss, 120% saline soil increase; illegal encroachment increased significantly
58	(Castillo et al., 2021)	The Sierra de San Miguelito Volcanic Complex (SSMVC) located in central Mexico	LULC & vegetation (INEGI, 2013); soil (INEGI, 2007); DEM (CEM 3.0: altitude, slope); geology; climate (CFSR, 1979–2013: rainfall, humidity, temperature); hydraulic conductivity; field data (66 points)	K-means clustering for grouping sampling points; PCA for dimensionality reduction; multivariate analysis (Z-score standardization, Spearman correlation); IDW interpolation for climate variables; GIS analysis using QGIS 3.4	Identification of dominant factors controlling groundwater recharge and delineation of recharge zones in the Sierra de San Miguelito Volcanic Complex using K-means, PCA, and geospatial analysis to assess its role as a recharge source for the San Luis Potosí Valley aquifer	Statistical validation using KMO (0.77), Bartlett's test ($p<0.05$), Shapiro-Wilk test for normality, and Kolmogorov-Smirnov test for distribution fitting; no AUC/R ² /ROC applied	Three clusters identified: Cluster 2 (48%) shows high recharge potential; Clusters 1 (23%) & 3 (29%) show low potential; PCA revealed 4 components explaining 77.88% variance; dominant factors include geology, hydraulic conductivity, temperature, precipitation, PET, humidity, and land use; strong correlations observed (Temp–PET: 0.93, Temp–Humidity: -0.89); overall, SSMVC has limited effectiveness as a groundwater recharge zone due to low porosity and unfavorable geology
59	(Khan et al., 2021)	The Karak watershed is located in Northern Pakistan	DEM (ASTER 30 m, SRTM); rainfall (PMD); Landsat 8 OLI; geology maps; LULC (FCMP); soil (DGSC); groundwater levels (32 wells,	MIF (multi-criteria decision model); weighted overlay analysis (ArcGIS 10.4) using 9 factors; ERT (dipole–dipole) and VES (Schlumberger) for	Assessment of groundwater potential in the Karak watershed using integrated geospatial and hydro-geophysical methods; characterization of	ROC-AUC = 0.68; overall accuracy = 68%; Kappa = 0.65; validation using groundwater level data (32 wells, pre- & post-monsoon);	Groundwater potential: Low (9.7%), Medium (52.4%), High (31.3%), Very High (6.6%); key factors: geology, lineament density, LULC; ERT resistivity (3.62–792 Ω m) identified aquifer layers; VES revealed 3–6 layer structures;

			2009–2019); geophysical data (ERT, VES); well logs (NRL, SPL)	subsurface analysis; ROC curve for validation; GIS-based spatial analysis	aquifer properties and identification of suitable sites for groundwater extraction and sustainable management	ERT/VES results correlated with borehole lithology	groundwater levels ranged 5.9–32.6 mbgl with fluctuations up to 19.3 m; agriculture dominant (62%); integrated MIF + geophysical approach showed satisfactory performance
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*Abbreviations used in each row of the table :**OLI** (Operational Land Imager), **SRTM** (Shuttle Radar Topography Mission), **DEM** (Digital Elevation Model), **NGSA** (Nigerian Geological Survey Agency), **NASA-IDW** (National Aeronautics and Space Administration - Inverse Distance Weighting), **LULC** (Land Use/Land Cover), **LST** (Land Surface Temperature), **MCDA-AHP** (Multi-Criteria Decision Analysis - Analytical Hierarchy Process), **CR** (Consistency Ratio), **WLC** (Weighted Linear Combination), **GIS** (Geographic Information System), **SI** (Sensitivity Analysis), **VIF** (Variance Inflation Factor), **GPZ** (Groundwater Potential Zone), **TM/ETM+** (Thematic Mapper/Enhanced Thematic Mapper Plus), **NDVI** (Normalized Difference Vegetation Index), **CHIRPS** (Climate Hazards Group InfraRed Precipitation with Station data), **FAO** (Food and Agriculture Organization), **GPS** (Global Positioning System), **RUSLE** (Revised Universal Soil Loss Equation), **SLM** (Sustainable Land Management), **IRS LISS-III** (Indian Remote Sensing Satellite - Linear Imaging Self-Scanning Sensor III), **SOI** (Survey of India), **TRMM** (Tropical Rainfall Measuring Mission), **IMD** (India Meteorological Department), **HEC-HMS** (Hydrologic Engineering Center's Hydrologic Modeling System), **SCS-CN** (Soil Conservation Service - Curve Number), **CWC** (Central Water Commission), **CMS** (Cubic Meters per Second), **ENVI** (Environment for Visualizing Images), **ROI** (Region of Interest), **ASTER** (Advanced Spaceborne Thermal Emission and Reflection Radiometer), **ESA/UCL** (European Space Agency / Université Catholique de Louvain), **SOTERCAF** (Soil and Terrain Database for Central Africa), **ISRIC** (International Soil Reference and Information Centre), **SVM** (Support Vector Machine), **SAR** (Synthetic Aperture Radar), **ECa** (Apparent Electrical Conductivity), **MERIT** (Multi-Error-Removed Improved-Terrain), **AI** (Aridity Index), **PET** (Potential Evapotranspiration), **RFE** (Recursive Feature Elimination), **LR** (Logistic Regression), **OM/SM** (Optimized Model/Simplified Model), **SMOTE** (Synthetic Minority Over-sampling Technique), **ROC-AUC** (Receiver Operating Characteristic - Area Under Curve), **SHAP** (Shapley Additive Explanations), **LandIS** (Land Information System), **NSI** (National Soil Inventory), **NatMap** (National Soil Map), **CEH** (Centre for Ecology & Hydrology), **UKCP09** (UK Climate Projections 2009), **PAM** (Phosphate Acceptance Map), **PCA** (Principal Component Analysis), **ETc** (Crop Evapotranspiration), **HWSD** (Harmonized World Soil Database), **MAR** (Managed Aquifer Recharge), **TDS** (Total Dissolved Solids), **CNN** (Convolutional Neural Network), **MCE** (Multi-Criteria Evaluation), **MAE** (Mean Absolute Error), **ISO/IEC** (International Organization for Standardization / International Electrotechnical Commission), **CGWB** (Central Ground Water Board), **GWPI** (Groundwater Potential Index), **RCC** (Rajshahi City Corporation), **GEOGLOWS** (Global Water Sustainability), **NDWI/MNDWI** (Normalized Difference Water Index / Modified NDWI), **MBWI** (Multi-band Water Index), **AWEI** (Automated Water Extraction Index), **AAS** (Atomic Absorption Spectroscopy), **EC** (Electrical Conductivity), **SSP** (Shared Socioeconomic Pathways), **ERA5** (ECMWF Reanalysis v5), **NSE** (Nash-Sutcliffe Efficiency), **RMSE** (Root Mean Square Error), **ESRI** (Environmental Systems Research Institute), **WOI** (Weighted Overlay Index), **UMSC** (Upper Manyame Sub-Catchment), **LD** (Lineament

Density), **TWI** (Topographic Wetness Index), **GWRZ** (Groundwater Recharge Zones), **WOA** (Weighted Overlay Analysis), **DD** (Drainage Density), **SSEBop** (Simplified Surface Energy Balance Operational), **PRISM** (Parameter-elevation Regressions on Independent Slopes Model), **ADWR** (Arizona Department of Water Resources), **AGRI/URBAN/SW** (Agriculture/Urban/Surface Water), **WD** (Withdrawal), **NRMSE/NMAE** (Normalized RMSE / Normalized MAE). **PCRWR** (Pakistan Council of Research in Water Resources), **DRASTICA** (DRASTIC + Anthropogenic), **RBF** (Radial Basis Function), **MDI** (Modified DRASTIC Index), **CPEC** (China-Pakistan Economic Corridor), **RSM** (Response Surface Methodology), **ERI** (Ecological Risk Index), **VES** (Vertical Electrical Sounding), **LGA** (Local Government Area), **CILSS** (Permanent Interstate Committee for Drought Control in the Sahel), **SPAM** (Spatial Production Allocation Model), **Mha** (Million Hectares), **MLP** (Multi-Layer Perceptron), **DT** (Decision Tree), **CONUS** (Continental United States), **NHGF** (National Hydrologic Geospatial Fabric), **NLDAS/GLDAS** (North American/Global Land Data Assimilation System), **XGB/HGB/LGBM** (Extreme/Hist-based/Light Gradient Boosting Machine), **AMC** (Antecedent Moisture Condition), **HI** (Hypsometric Index), **WRIS** (Water Resources Information System), **MCC** (Matthews Correlation Coefficient), **CEAP** (Conservation Effects Assessment Project), **AGWA** (Automated Geospatial Watershed Assessment), **RaBET** (Rangeland Brush Estimation Tool), **NMDS** (Non-metric Multidimensional Scaling), **SATVI** (Soil Adjusted Total Vegetation Index), **MCM** (Million Cubic Meters), **PBS** (Pakistan Bureau of Statistics), **BARC** (Bangladesh Agricultural Research Council), **CMIP6** (Coupled Model Intercomparison Project Phase 6), **DSS** (Decision Support System), **SBAS-InSAR** (Small Baseline Subset InSAR), **BiLSTM** (Bidirectional LSTM), **TWSA** (Terrestrial Water Storage Anomaly), **EVI/LAI/FPAR** (Enhanced Vegetation Index / Leaf Area Index / Fraction of Photosynthetically Active Radiation), **GPP** (Gross Primary Productivity), **MAPE** (Mean Absolute Percentage Error), **ICIMOD** (International Centre for Integrated Mountain Development), **TPI** (Topographic Position Index), **PERSIANN-CDR** (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record), **RTE/FVD/SVD/AS-FFT** (Reduced to Pole / First Vertical Derivative / Second Vertical Derivative / Analytic Signal-Fast Fourier Transform), **AMPA** (Aminomethylphosphonic acid), **UHPLC-MS/MS** (Ultra-High Performance Liquid Chromatography - Tandem Mass Spectrometry), **LOQ** (Limit of Quantitation), **IWMP** (Integrated Watershed Management Project), **POI** (Point of Interest), **SHP** (Small Hydropower), **MTA** (General Directorate of Mineral Research and Exploration - Turkey), **DSİ** (State Hydraulic Works), **HGM/MAF** (General Directorate of Mapping / Mean Annual Flow), **DPSIR** (Driver-Pressure-State-Impact-Response), **LUCC** (Land Use/Cover Change), **CA-Markov** (Cellular Automata-Markov), **LCM** (Land Change Modeler), **SSMVC** (Sierra de San Miguelito Volcanic Complex), **INEGI** (National Institute of Statistics and Geography - Mexico), **CFSR** (Climate Forecast System Reanalysis), **KMO** (Kaiser-Meyer-Olkin), **MIF** (Multi-Influence Factor), **ERT** (Electrical Resistivity Tomography), **mbgl** (meters below ground level).

Table 8. Studies included in regression analysis 1: field validation point count and ROC-AUC. Validation points (n) = number of boreholes, wells, or springs used for model validation; ROC-AUC = Area Under the Receiver Operating Characteristic Curve; RF = Random Forest; AHP = Analytical Hierarchy Process; MIF = Multi-Influence Factor.

S. No	Author & Year	Country / Region	Primary Method	Validation Points (n)	ROC-AUC
S54	Gulbet Tebege et al., 2025	Ethiopia	AHP-GIS	11	0.604
S14	Sharma & Singh, 2025	India	AHP-GIS	13	0.805
S42	Ishola et al., 2023	Nigeria	AHP-GIS	20	0.730
S43	Shekar et al., 2025	India	AHP-GIS	30	0.810
S59	Khan et al., 2021	Pakistan	MIF-GIS	32	0.680
S08	Ray, 2025	India	AHP-TOPSIS	33	0.850
S20	Balasubramaniyan et al., 2025	India	AHP-GIS	51	0.830
S41	Poudel et al., 2024	Nepal	AHP-GIS	56	0.707
S33	Takele et al., 2025	Ethiopia	AHP + SWAT	80	0.800
S31	Anand et al., 2025	India	RF (ML)	136	0.910
Mean	—	—	—	45.2	0.773

* Validation points (n) = number of boreholes, wells, or springs used for field-based model validation. ROC-AUC = Area Under the Receiver Operating Characteristic Curve. RF = Random Forest; AHP = Analytical Hierarchy Process; MIF = Multi-Influence Factor; TOPSIS = Technique for Order Preference by Similarity to Ideal Solution. S. No = Study number as assigned in Table 7 of this systematic review

Table .9 Studies included in regression analysis 2: thematic input layer count and ROC-AUC. Thematic Layers (n) = number of conditioning factors integrated into the AHP/MCDA model; ROC-AUC = Area Under the Receiver Operating Characteristic Curve.

S. No	Author & Year	Country / Region	Thematic Layers (n)	ROC-AUC
S42	Ishola et al., 2023	Nigeria	7	0.730
S14	Sharma & Singh, 2025	India	7	0.805
S22	Shandu & Atif, 2023	S. Africa	7	0.790
S16	Rajasekhar et al., 2022	India	8	0.780
S54	Gulbet Tebege et al., 2025	Ethiopia	9	0.604
S59	Khan et al., 2021	Pakistan	9	0.680
S43	Shekar et al., 2025	India	10	0.810
S33	Takele et al., 2025	Ethiopia	10	0.800
S20	Balasubramaniyan et al., 2025	India	10	0.830
S08	Ray, 2025	India	12	0.850
Mean	—	—	8.9	0.768

* CR = AHP Consistency Ratio (all studies reported CR < 0.10, confirming reliable pairwise weighting). Mean row shaded for visual reference.

Table 10. Summary of mean ROC-AUC by analytical method family across studies included in the meta-regression analysis. Performance level classification: AUC 0.70–0.79 = Acceptable; 0.80–0.89 = Good; and ≥ 0.90 = Excellent.

Method Family	n Studies	Mean ROC-AUC	Min AUC	Max AUC	Performance Level
AHP-only	7	0.748	0.604	0.830	Acceptable–Good
AHP-hybrid	3	0.815	0.795	0.850	Good
ML/Ensemble	2	0.860	0.810	0.910	Good–Excellent
Overall	12	0.773	0.604	0.910	—

* AHP: Analytical Hierarchy Process; ML: Machine Learning. The AHP-hybrid includes studies augmenting AHP with TOPSIS, SWAT, or GIS-based flood modelling. Error ranges represent observed min–max, not standard deviation, because of the small n per group.

Table 11. Methodological quality and risk of bias assessment for representative geospatial studies evaluated across spatial resolution, temporal consistency, and validation integrity.

Study ID	Author & Year	Spatial Bias (Resolution)	Temporal Bias (Consistency)	Model Bias (Validation Metrics)	Source Bias (Ground Truth)	Selection Bias
S01	(Ozegin et al., 2024)	Low (Sentinel-2, 10m)	High (Seasonal)	High (R ² =0.911)	High (21 Borehole points)	Low
S05	(Valencia-Ortiz et al., 2026)	Low (Sentinel-1/2, 10m)	Moderate	High (AUC=0.73)	High (361 soil samples)	Low
S08	(Ray, 2025)	Moderate (Landsat, 30m)	Low (Static)	High (AUC=0.85)	High (33 well points)	Low
S11	(Firoz et al., 2026)	Low (Sentinel-2, 10m)	High (Decadal)	Moderate (OA > 85%)	Moderate (GPS/Lab)	Low
S15	(Wagoneka et al., 2025)	Moderate (Landsat, 30m)	High (1980–2020)	High (R ² =0.715\$)	High (713 boreholes)	Low
S20	(Balasubramaniyan et al., 2025)	Moderate (DEM/Landsat)	Low	High (AUC=0.83)	High (51 borewells)	Low
S28	(Feng et al., 2025)	Moderate (Landsat/DEM)	Low (Event-based)	High (Acc: 95.76%)	High (235 inventory pts)	Low
S29	(Modaresi Rad et al., 2024)	Low (NHD/NWM)	High (Long-term)	High (R ² =0.80)	High (>200k sites)	Low
S33	(Takele et al., 2025)	Moderate (Landsat/DEM)	High (1982–2016)	High (AUC=0.80)	High (80 water points)	Low
S39	(Dasari et al., 2025)	Low (Sentinel-2, 10m)	High (Seasonal)	High (R ² =0.82)	High (CWC observed)	Low
S43	(Shekar et al., 2025)	Moderate (SRTM/ESRI)	Low	High (AUC=0.81)	Moderate (30 wells)	Low
S52	(Korkmaz, 2026)	Moderate (Landsat, 30m)	High (1992–2022)	Moderate (OA: 88–92%)	Moderate (Google Earth)	Low
S56	(Luo et al., 2023)	Moderate (Landsat, 30m)	High (1995–2020)	Moderate (OA > 88%)	High (Google Earth samples)	Low
S59	(Khan et al., 2021)	Moderate (ASTER, 30m)	Moderate	Low (AUC=0.68)	Moderate (32 wells/ERT)	Moderate

Table 12. Optical and microwave satellite datasets for LULC classification

Data Type	Dataset / Source	Spatial Resolution	Key Spectral Bands / Features	Primary Applications in LULC	Reference
Optical	Sentinel-2 (MSI)	10–20 m	Coastal (B1), Blue (B2), Green (B3), Red (B4), Red Edge (B5–B7), NIR (B8, B8A), SWIR (B11, B12)	LULC classification, crop mapping, vegetation analysis, water body extraction	(Saini & Ghosh, 2018)
Optical	Landsat (5, 7, 8, 9)	30 m (optical), 100 m (thermal)	Coastal, Blue, Green, Red, NIR, SWIR-1, SWIR-2, Thermal bands	Long-term LULC change detection, urban mapping, environmental monitoring	(Baidoo & Obeng, 2023)
Optical	MODIS	250 m – 1 km	Red, NIR, Blue, Green, SWIR, Thermal bands	Large-scale LULC mapping, vegetation dynamics, drought monitoring	(Ehsan & Kazem, 2013)
Optical	WorldView-2/3	0.3–2 m	Coastal, Blue, Green, Yellow, Red, Red Edge, NIR1, NIR2	High-resolution urban mapping, infrastructure detection	(Verone Wojtaszek et al., 2021)
Optical	PlanetScope	3–5 m	Blue, Green, Red, NIR	Crop monitoring, high-frequency LULC updates	(Şimşek, 2025)
Optical	VIIRS	~375 m	Visible, NIR, Thermal bands	Night-time lights, urban expansion analysis	(Schroeder et al., 2014)
Microwave (SAR)	Sentinel-1	~10 m	C-band SAR (VV, VH polarization)	Flood mapping, soil moisture, all-weather LULC classification	(Fan et al., 2025)
Microwave (SAR)	ALOS PALSAR	10–25 m	L-band SAR (HH, HV polarization)	Forest mapping, biomass estimation, land degradation analysis	(Achmad et al., 2013)
Microwave (SAR)	RADARSAT	10–100 m	C-band SAR	Surface roughness, wetland mapping, disaster monitoring	(Moon et al., 2010)
Hyperspectral (Optical Advanced)	PRISMA / EnMAP	30 m	Hundreds of narrow spectral bands	Detailed crop classification, soil property mapping, material identification	(Moorthi et al., 2025)

Table 13. Datasets for Land Capability and Suitability Analysis

Data Category	Dataset / Source	Spatial Resolution	Key Features / Data Provided	Applications in Land Suitability Analysis	Reference
Optical Satellite Data	Sentinel-2 (MSI)	10–20 m	Blue (B2), Green (B3), Red (B4), Red Edge (B5–B7), NIR (B8), SWIR (B11, B12)	LULC mapping, vegetation health, crop suitability	(Nguyen et al., 2020)
	Landsat (5, 7, 8, 9)	30 m	Multispectral + thermal bands	Land use change, evapotranspiration, soil moisture proxy	(Nguyen Thu Thuy et al., 2024)
Microwave (SAR)	Sentinel-1	~10 m	C-band SAR (VV, VH)	Soil moisture estimation, surface roughness	(Bulut et al., 2024)
Topographic Data	SRTM / ASTER DEM	~30 m	Elevation, slope, aspect	Terrain suitability, erosion risk, drainage	(Forkuo & Maathuis, 2012)
Soil Data	FAO Soil Map / ISRIC SoilGrids	250 m – 1 km	Soil texture, pH, organic carbon, depth	Soil suitability for crops and land capability	(Hengl et al., 2017)
Climate Data	CHIRPS / ERA5 / WorldClim	~1 km – 30 km	Rainfall, temperature, evapotranspiration	Agro-climatic suitability assessment	(Das et al., 2025a)
Land Surface Temperature	Landsat Thermal Bands	100 m (resampled 30 m)	Surface temperature	Crop suitability, stress analysis	(Nicolòs et al., 2023)
Vegetation Data	MODIS NDVI	250 m	Vegetation dynamics	Productivity and land capability	(Wardlow et al., 2007)
Infrastructure Data	OpenStreetMap (OSM)	Variable	Roads, settlements	Accessibility, market proximity	(Hosseini et al., 2025a)
Socio-economic Data	Census / WorldPop	100 m – 1 km	Population density, land use pressure	Planning and decision-making	(Metzger et al., 2024)
Hydrological Data	DEM + CHIRPS	Variable	Drainage, runoff, water availability	Irrigation suitability	(Akpoti et al., 2022)

Table 14. Land Suitability Criteria, Indices, and Data Sources (MCE Inputs)

Suitability Parameter	Index / Method	Bands / Data Used (Dataset-Specific)	Role in Suitability Analysis	Reference
Land Use / Land Cover	Supervised Classification	Sentinel-2: B2, B3, B4, B8 Landsat: B2–B5	Identifies suitable land categories	(Abida et al., 2022)
Vegetation Health	$NDVI = (NIR - Red) / (NIR + Red)$	Sentinel-2: B8, B4 Landsat: B5, B4	Indicates productivity potential	(Qin et al., 2021)
Slope	Slope analysis	DEM (SRTM/ASTER)	Determines cultivation suitability	(Jing et al., 2014)
Elevation	DEM analysis	DEM	Influences climate and crop growth	(Ma et al., 2020)
Soil Texture & Type	Soil classification	SoilGrids / FAO	Determines water retention and fertility	(Usman & Jayeoba, 2025)
Soil Moisture	SAR backscatter	Sentinel-1: VV, VH	Indicates water availability	(Rahmati et al., 2026)
Rainfall	Interpolation	CHIRPS / WorldClim	Determines crop suitability	(Das et al., 2025b)
Temperature	Climate analysis	ERA5 / WorldClim	Growth condition assessment	(Yilmaz, 2023)
Drainage	Hydrological modelling	DEM	Affects water availability and flooding	(Nishio & Mori, 2015)
Distance to Roads	Buffer analysis	OSM data	Accessibility and transport cost	(Hosseini et al., 2025b)
Distance to Water Sources	Proximity analysis	Rivers / DEM	Irrigation suitability	(Abadefar, 2025)
Land Surface Temperature	LST models	Landsat B10, B11	Crop stress and suitability	(Ullah et al., 2023)
Multi-Criteria Evaluation	AHP, Fuzzy AHP, TOPSIS, OWA	All thematic layers	Final suitability zoning	(Eghbali Lord et al., 2025)

Table 15 .Overview of geospatial data sources used in land use planning and zoning, data categories, spatial resolution, key features and applications.

Data Category	Dataset / Source	Spatial Resolution	Key Features / Data Provided	Applications in Land Use Planning & Zoning	reference
Optical Satellite Data	Sentinel-2 (MSI)	10–20 m	Multispectral (Blue, Green, Red, NIR, SWIR)	LULC mapping, urban expansion, green space analysis	(Gülci et al., 2025)
	Landsat (5, 7, 8, 9)	30 m	Long-term multispectral + thermal	Urban growth analysis, land use change detection	(Duan et al., 2025)
	PlanetScope	3–5 m	High-resolution optical imagery	Detailed urban zoning, infrastructure mapping	(Alawathugoda et al., 2024)
Night-Time Data	VIIRS Night Lights	~375 m	Night-time light intensity	Urbanization level, economic activity mapping	(Ivan et al., 2020)
Microwave (SAR)	Sentinel-1	~10 m	C-band SAR (VV, VH)	Built-up area detection, flood-prone zoning, surface roughness	(Toma et al., 2024)
Topographic Data	SRTM / ASTER DEM	~30 m	Elevation, slope, aspect	Suitability analysis, infrastructure planning, hazard zoning	(Huang & Yu, 2024)
Population Data	WorldPop / Census Data	100 m – 1 km	Population density, distribution	Urban planning, service allocation, zoning regulations	(Song et al., 2024)
Infrastructure Data	OpenStreetMap (OSM)	Variable	Roads, buildings, utilities	Transport planning, urban zoning, accessibility analysis	(Hosseini et al., 2025a)
Land Records / Cadastral Data	Government land records	Parcel level	Ownership, land parcels	Legal zoning, land-use regulation	(Cienciała et al., 2021)
Environmental Data	Air quality (Sentinel-5P), Climate data (ERA5)	Variable	Pollution, temperature, rainfall	Environmental zoning, sustainable planning	(Shah et al., 2024)
Hazard Data	Flood (Sentinel-1), Landslide maps	Variable	Risk zones	Disaster risk zoning, land-use restrictions	(Shahabi et al., 2020)
Decision Support Data	SDSS / GIS layers	Multi-source	Integrated spatial layers	Policy making, zoning decisions, urban planning models	(Li & Yan, 2025)

Table 16. Overview of remote sensing datasets used for water quality monitoring, including spectral characteristics, spatial resolution, and key applications

Data Type	Dataset / Source	Spatial Resolution	Key Spectral Bands / Features	Applications in Water Quality Monitoring	Reference
Optical	Sentinel-2 (MSI)	10–20 m	Blue (B2), Green (B3), Red (B4), Red Edge (B5–B7), NIR (B8), SWIR (B11, B12)	Turbidity, chlorophyll, suspended sediment, inland water quality monitoring	(Arbab Mullick et al., 2025)
Optical	Landsat (8/9 OLI/TIRS)	30 m	Blue, Green, Red, NIR, SWIR, Thermal	Water quality assessment, surface temperature, long-term monitoring	(Eon et al., 2023)
Optical	MODIS	250 m – 1 km	Visible, NIR, SWIR, Thermal bands	Large-scale monitoring, ocean color, algal bloom detection	(Hu et al., 2010)
Optical	Sentinel-3 (OLCI/SLSTR)**	300 m – 1 km	Ocean color bands, thermal bands	Coastal and ocean water quality, chlorophyll, sea surface temperature	(Rodrigues et al., 2022)
Optical	PlanetScope	3–5 m	Blue, Green, Red, NIR	High-resolution monitoring of small water bodies	(Yigit Aydan et al., 2019)
Microwave (SAR)	Sentinel-1	~10 m	C-band SAR (VV, VH)	Flood detection, surface water extent, indirect water quality support	(S.-Y. Kim et al., 2025)
Microwave (SAR)	RADARSAT	10–100 m	C-band SAR	Wetland mapping, water extent monitoring	(Adeli et al., 2020)
Hyperspectral	PRISMA / EnMAP	30 m	Narrow continuous spectral bands	Detailed analysis of chlorophyll, dissolved organic matter, water constituents	(Chabrillat et al., 2024)

Table 17. Key water quality parameters and their significance in environmental monitoring and assessment.

Water Quality Parameter	Index / Method	Bands Used (Dataset-Specific)	Purpose	Reference
Water Presence / Extent	$NDWI = (Green - NIR) / (Green + NIR)$	Sentinel-2: B3, B8 Landsat 8/9: B3, B5	Delineation of water bodies	(Jiang et al., 2021)
Modified Water Index	$MNDWI = (Green - SWIR) / (Green + SWIR)$	Sentinel-2: B3, B11 Landsat 8/9: B3, B6	Improved water extraction in urban areas	(Du et al., 2016)
Turbidity	$NDTI = (Red - Green) / (Red + Green)$	Sentinel-2: B4, B3 Landsat 8/9: B4, B3	Suspended sediment and turbidity detection	(Lizcano-Sandoval et al., 2022)
Chlorophyll-a	Band ratio (Blue/Green, Green/Red)	Sentinel-2: B2/B3, B3/B4 Landsat 8/9: B2/B3, B3/B4	Estimation of algal concentration	(Jang et al., 2024)
Suspended Sediment	Empirical models (Red/NIR)	Sentinel-2: B4, B8 Landsat 8/9: B4, B5	Sediment load estimation	(Torres-Vera, 2023)
Water Clarity	Secchi Depth Models	Sentinel-2: B2, B3 Landsat 8/9: B2, B3	Water transparency assessment	(L. Yang et al., 2022)
Surface Temperature	LST (Thermal bands)	Landsat 8/9: B10, B11	Water temperature monitoring	(Vanhellemont, 2020)
Dissolved Organic Matter (DOM)	Spectral absorption models	Hyperspectral (PRISMA/EnMAP): Blue–UV range	Organic pollution detection	(Niroumand-Jadidi et al., 2020)
Algal Bloom Detection	$FAI = NIR - (Red + SWIR \text{ interpolation})$	Sentinel-2: B8, B4, B11 Landsat 8/9: B5, B4, B6	Harmful algal bloom monitoring	(M. Liu et al., 2021)
Trophic State	TSI (multi-band models)	Sentinel-2: B2, B3, B4 Landsat 8/9: B2, B3, B4	Nutrient enrichment assessment	(Zhou et al., 2021)
Water Depth (Bathymetry)	Band ratio (Blue/Green)	Sentinel-2: B2, B3 Landsat 8/9: B2, B3	Shallow water depth estimation	(Ichsan et al., 2026)
CDOM (Colored DOM)	Blue/UV spectral models	Sentinel-2: B2 Hyperspectral sensors	Water quality and pollution analysis	(G. Liu et al., 2021)

Table 18. Key geospatial parameters, indices, and datasets used for groundwater potential mapping and their roles in influencing groundwater occurrence and recharge.

Category	Groundwater Parameter	Index / Method	Bands / Data Used (Dataset-Specific)	Role in Groundwater Mapping	Reference
Surface Characteristics	Land Use / Land Cover	Supervised Classification	Sentinel-2: B2, B3, B4, B8 Landsat: B2–B5	Controls infiltration, runoff, and recharge potential	(Mashala et al., 2026)
	Vegetation Cover	NDVI = $(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	Sentinel-2: B8, B4 Landsat: B5, B4	Indicates soil moisture and recharge zones	
Hydrological Factors	Drainage Density	GIS hydrological analysis	DEM (SRTM/ASTER)	High drainage → runoff; low drainage → infiltration	(T. Dar et al., 2021)
	Rainfall	Interpolation (IDW/Kriging)	CHIRPS / TRMM	Primary source of groundwater recharge	
Topographic Factors	Slope	Slope analysis	DEM (SRTM/ASTER)	Gentle slopes favor infiltration; steep slopes increase runoff	(M. C. Singh et al., 2023)
Subsurface & Structural Factors	Lineament Density	Lineament extraction	Sentinel-2 / Landsat / SAR	Indicates fractures and groundwater pathways	(Gaber et al., 2020)
	Lithology	Geological mapping	Satellite + geological maps	Determines aquifer properties and permeability	
	Geomorphology	Visual interpretation / classification	Sentinel-2 / Landsat	Identifies landforms controlling groundwater occurrence	
Soil & Moisture Conditions	Soil Moisture	SAR backscatter analysis	Sentinel-1: VV, VH	Indicates water retention and infiltration capacity	(Kondraju et al., 2025)
Storage & Regional Dynamics	Groundwater Storage	GRACE anomaly analysis	GRACE satellite	Monitors large-scale groundwater variation	(Verma et al., 2016)

Table 19. Identified research gaps, limitations, and future directions of geospatial technologies for environmental and resource management.

Gap Category	Current Status	Limitations Identified	Implications	Future Research Direction	Reference
Advanced Sensors (UAV, LiDAR, Hyperspectral)	Limited experimental use	High cost, limited scalability, lack of automation	Restricted large-scale application	Develop cost-effective and automated workflows	(X. Yang et al., 2025)
Real-Time Monitoring (IoT)	Rarely integrated	Lack of continuous in-situ data	Weak temporal accuracy	Integration of IoT with RS-GIS systems	(Fajri et al., 2025)
Cloud Computing (GEE)	Increasing usage	Mostly semi-automated workflows	Limited scalability and reproducibility	Fully automated geospatial pipelines	(Orusa et al., 2025)
AI/ML Integration	Widely used for classification	Limited use of in-situ data for validation	Reduced model reliability	Hybrid models combining RS + field data	(Demissie et al., 2026)
Data Fusion	Weak integration of datasets	Difficulty combining satellite, field, and crowdsourced data	Incomplete environmental assessment	Multi-source data fusion frameworks	(Gokaraju et al., 2017)
Spatial & Temporal Resolution	Inconsistent datasets	Temporal mismatch, limited high-resolution data	Reduced accuracy	Harmonization of multi-resolution datasets	(L. Yang et al., 2020)

Table .20 Key methodological limitations of geospatial studies, their impact on results, and recommended improvements.

Limitation Category	Issue Identified	Examples	Impact on Results	Recommended Improvement
Lack of Standardization	Different methods across studies	LULC classification, drought indices (SPI, SPEI)	Poor comparability	Develop standardized protocols
Index Variability	Different indices produce different results	NDVI vs SPI vs SPEI	Inconsistent conclusions	Multi-index integration approach
Threshold Selection	Subjective thresholds	Classification thresholds	Bias in outputs	Data-driven threshold selection
Limited Predictive Modelling	Mostly descriptive studies	Mapping without forecasting	Low decision-making utility	Use ML, deep learning, MCDA
Single-Parameter Focus	Ignoring system interactions	Only NDVI or rainfall analysis	Oversimplified analysis	Multi-variable modelling
Validation Issues	Lack of ground truth data	Limited field data	Reduced accuracy	Integration of in-situ observations
Model Comparison Gaps	Few comparative studies	RF vs SVM vs DL	Weak benchmarking	Use benchmark datasets
Benchmark Dataset Absence	No common datasets	Case-specific studies	Low reproducibility	Develop open benchmark datasets

Table.21 Applications of artificial intelligence and geospatial techniques in environmental monitoring and resource management.

Application Area	Technique Used	Purpose / Function	Key Benefits	Reference
Plantation Mapping	Machine Learning (ML), Remote Sensing	Identification and mapping of plantation areas	High accuracy, rapid classification, large-scale analysis	(Segar et al., 2024)
Water Quality Monitoring	AI/ML Algorithms	Detection and prediction of water contaminants	Improved efficiency, early detection of pollution	(Shams et al., 2023)
Environmental Monitoring	AI + Geospatial Techniques	Monitoring land and water resources	Enhanced accuracy and data-driven decision-making	(Olawade et al., 2024)
Real-time Monitoring	Tiny Machine Learning (TinyML)	In situ environmental monitoring using microcontrollers	Low-cost, real-time data acquisition	(Bagheri et al., 2023b)
Spatial Analysis	Intelligent GIS, AI Integration	Advanced system-level analysis and modeling	Improved analytical capability and system integration	(Şekeroğlu & Çelik, 2025)
Resource Management	ML + GIS + Remote Sensing	Sustainable land and water resource planning	Increased efficiency and predictive modeling	(Rabie et al., 2025)
Predictive Modeling	Machine Learning Algorithms	Forecasting environmental changes	Better decision support and risk assessment	(Ukoba et al., 2025)

Table.22 Applications of big data and geospatial technologies across different themes, highlighting tools, outcomes, and decision-support capabilities.

Theme	Application	Technologies Used	Outcome	Reference
Agriculture	Crop yield prediction	AI, RS, Big Data	Improved productivity forecasting	(Gadhiya, 2025)
Water Resources	Groundwater & surface water monitoring	GIS, Big Data	Efficient water management	(<u>Rahim et al., 2025</u>)
Environmental Monitoring	Climate & land degradation analysis	RS, Big Data	Sustainable environmental planning	((Hoang et al., 2026)
Data Processing	Large dataset handling	Apache Spark, Cloud Computing	Faster data processing	(Mittal et al., 2019)
Decision Support Systems	Resource planning	Big Data + GIS	Enhanced policy and planning support	(H. Y. Kim & Lee, 2014)

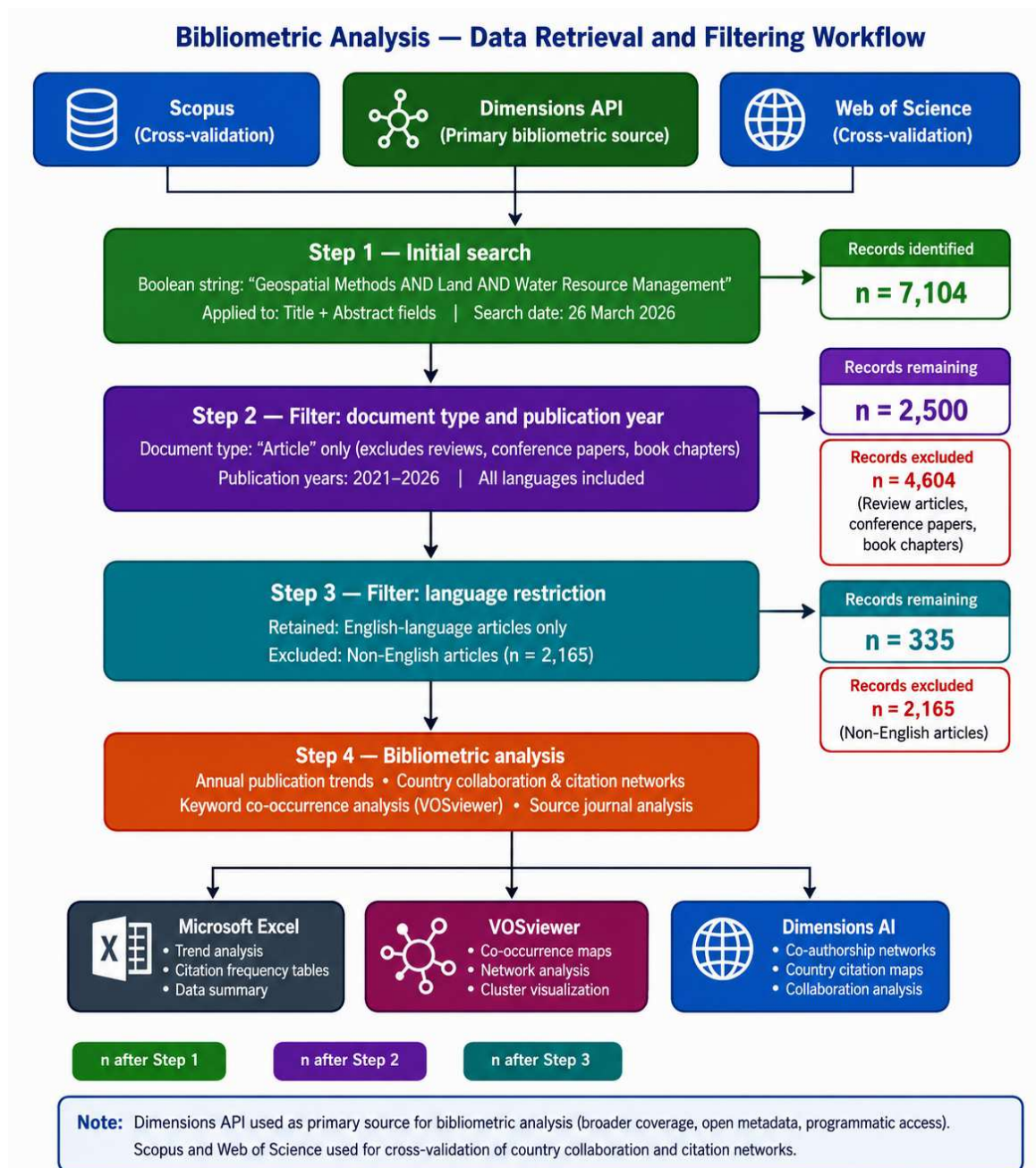


Fig. 1. Data retrieval and filtering workflow for the bibliometric analysis. The three sequential filtering steps explain the three publication counts cited in the text: $n = 7,104$ (all document types, all years, all languages); $n = 2,500$ (articles only, 2021–2026, all languages); and $n = 335$ (articles only, 2021–2026, English only — final analytical dataset). Dimensions API was used as the primary data source; Scopus and Web of Science were used for cross-validation only.

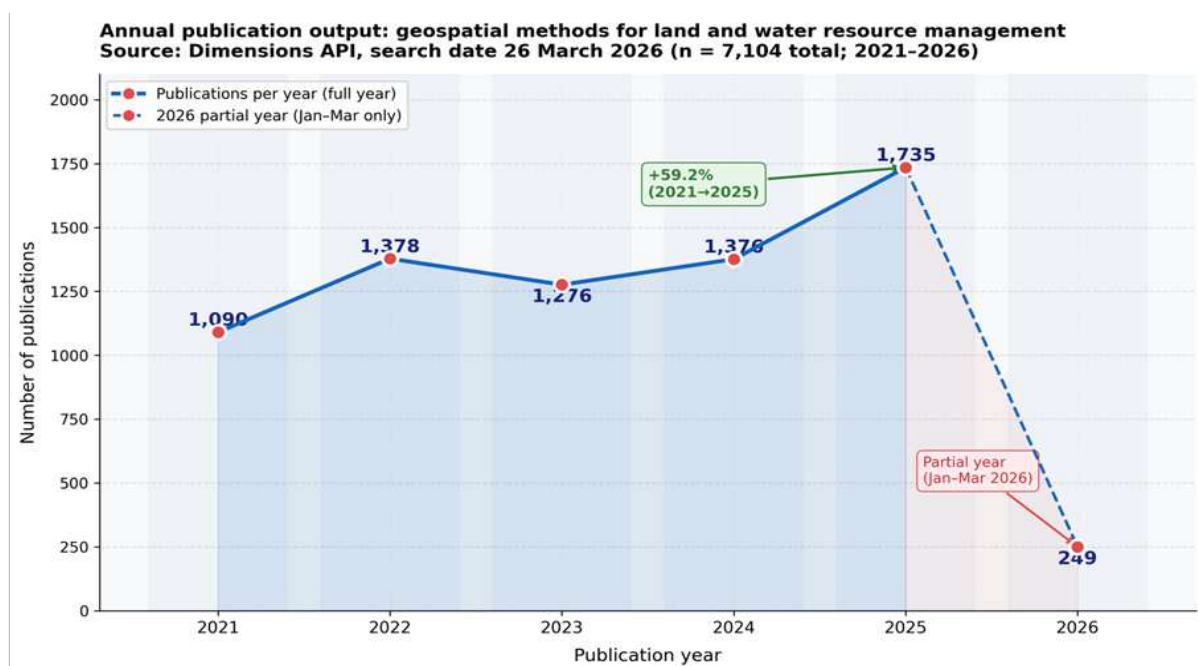


Fig.2. Annual publication output of geospatial methods in land and water resource management research (2021–2026). Source: Dimensions API; total publications retrieved across all document types for the Boolean search string (n = 7,104). Solid line = full-year data (2021–2025); dashed line = partial year 2026 (January–March only; search date: March 26, 2026). Red annotation: +59.2% growth from the 2021 to 2025 peak (1,090 → 1,735 publications). 2026 (n = 249) were excluded from the trend calculations and are shown for reference only.

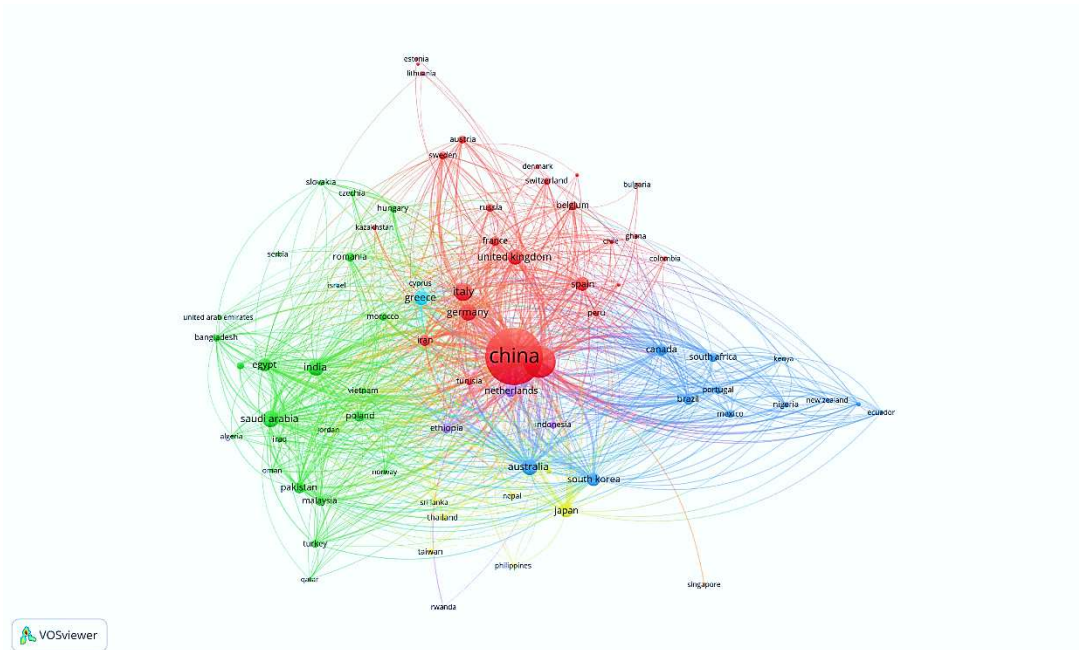


Fig.3 Country Linkage network of research in geospatial methods for land and water resource management. *The map, generated using VOSviewer, illustrates global research collaborations grouped into clusters, where the node size represents publication output, link thickness indicates collaboration strength, and colors denote different research clusters. China was the most prominent and highly connected country.*

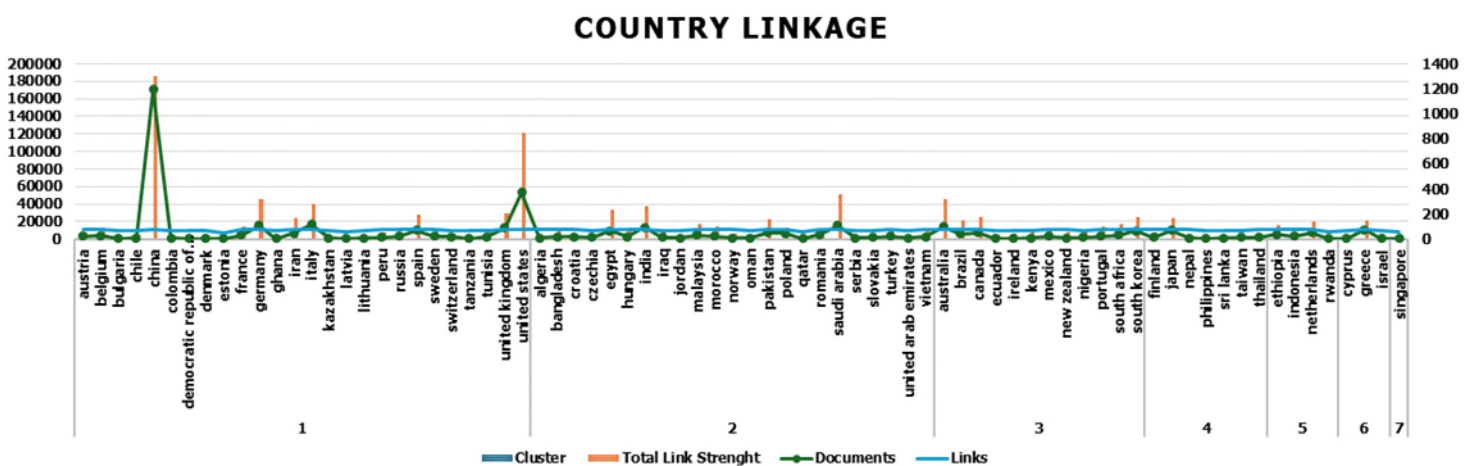


Fig.4 Country-wise linkage analysis showing clusters, total link strength, number of documents, and collaboration links in geospatial research for land and water resource management. The figure highlights variations in research productivity and collaboration

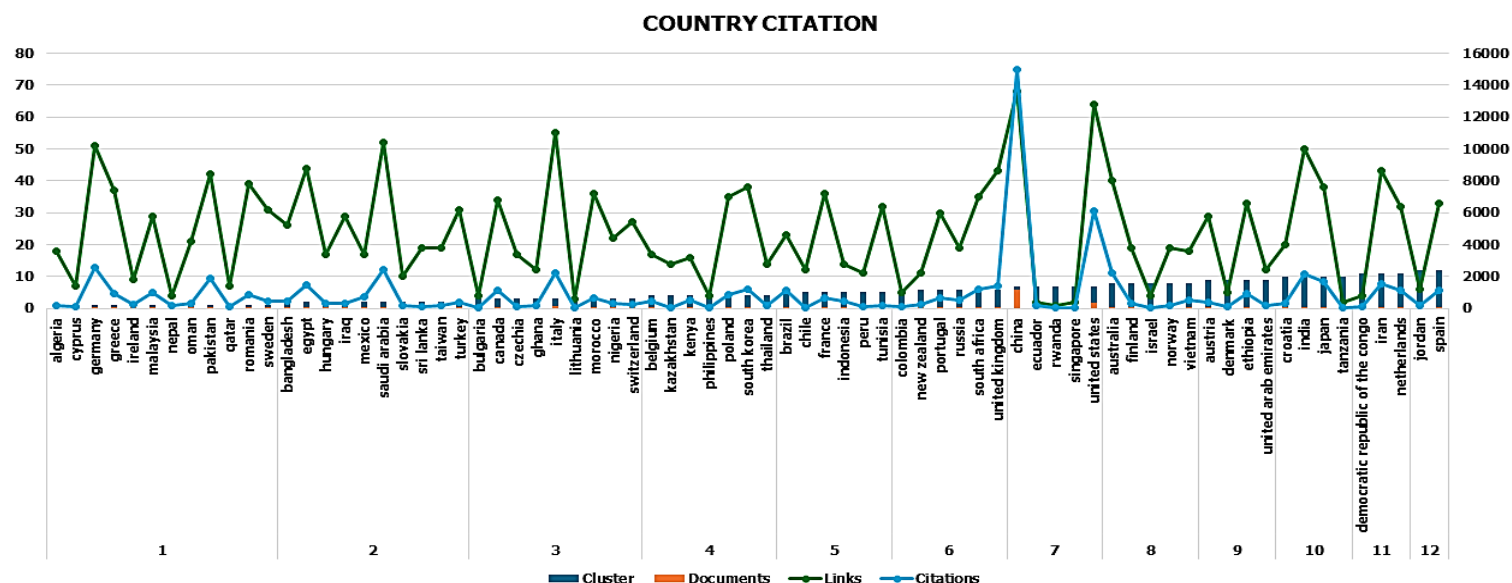


Fig.5 Country-wise citation analysis showing the distribution of documents, links, and citations across clusters in geospatial research for land and water resource management. The figure highlights variations in citation impact among countries, with highly cited nations demonstrating stronger research influence and collaboration.

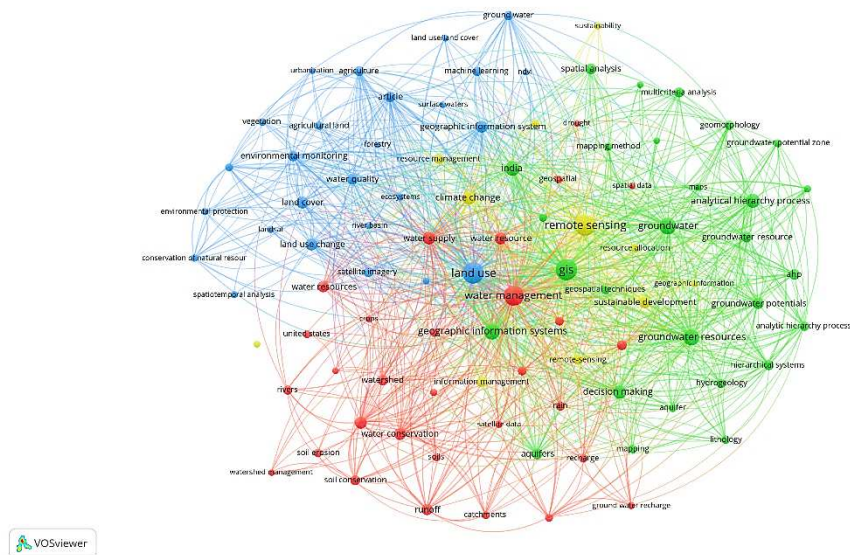


Fig.6 Keyword co-occurrence network of geospatial research in land and water resource management. The map, generated using VOSviewer, illustrates the relationships among frequently used keywords, where node size represents keyword frequency, link strength indicates co-occurrence relationships, and colors denote thematic clusters such as remote sensing, GIS, groundwater, and land use.

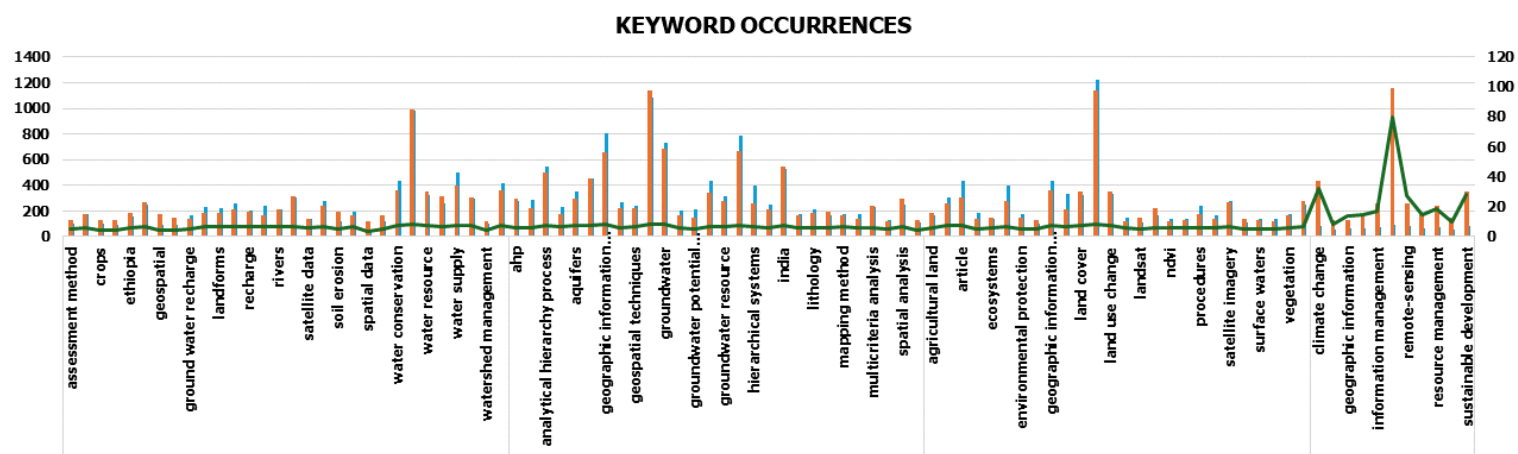


Fig.7 Keyword occurrence analysis showing the distribution of keyword frequency, total link strength, and link connections across clusters in geospatial research for land and water resource management. The figure highlights dominant keywords and their relative importance within different thematic clusters.

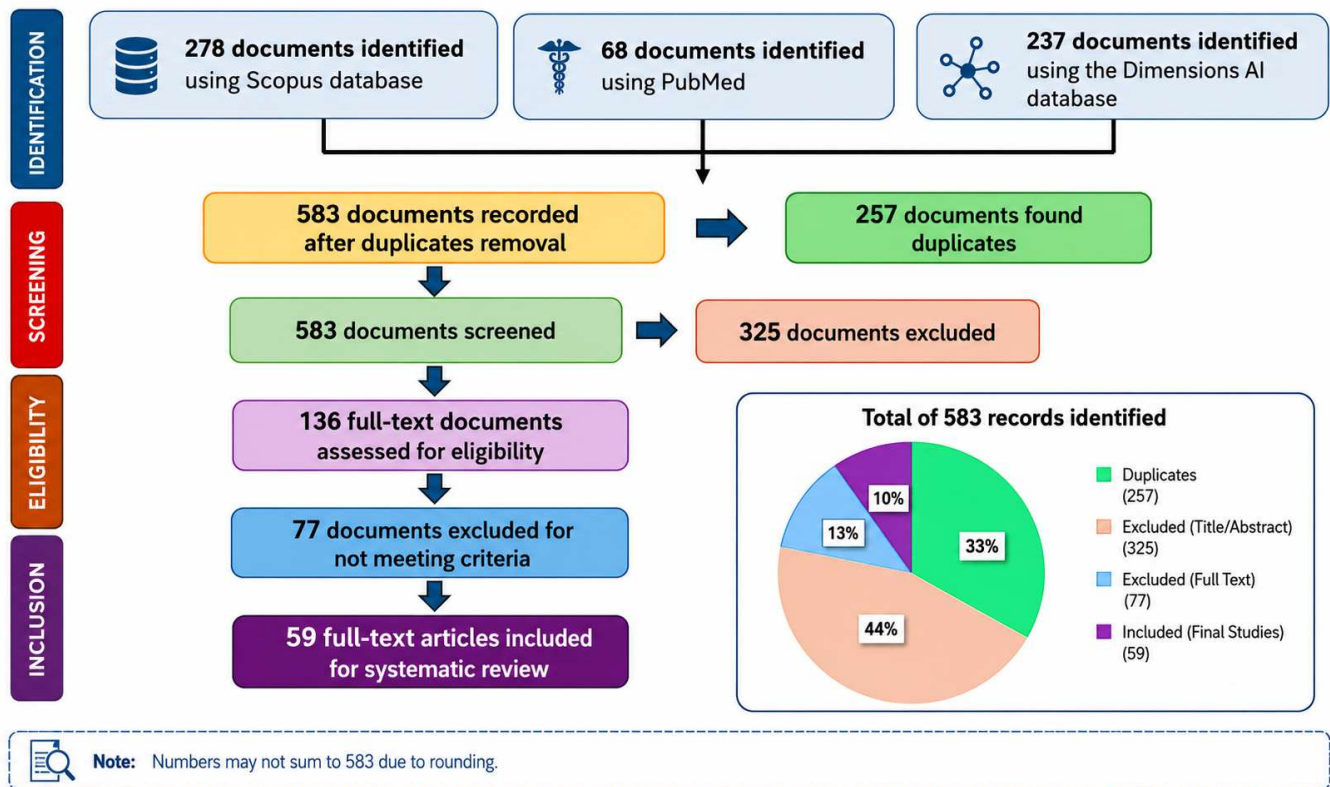


Fig. 8. PRISMA 2020 flow diagram illustrating the systematic literature search, screening, eligibility assessment, and final inclusion process. Total records identified across all databases: $n = 583$. Records after duplicate removal: $n = 326$. Records screened by title and abstract: $n = 326$. Full-text articles assessed for eligibility: $n = 136$. The final studies included in the systematic review were 59. The inset pie chart shows the proportional distribution of all identified records by the disposition category. Records were obtained from Scopus ($n = 278$), PubMed ($n = 68$), and Dimensions AI ($n = 237$).

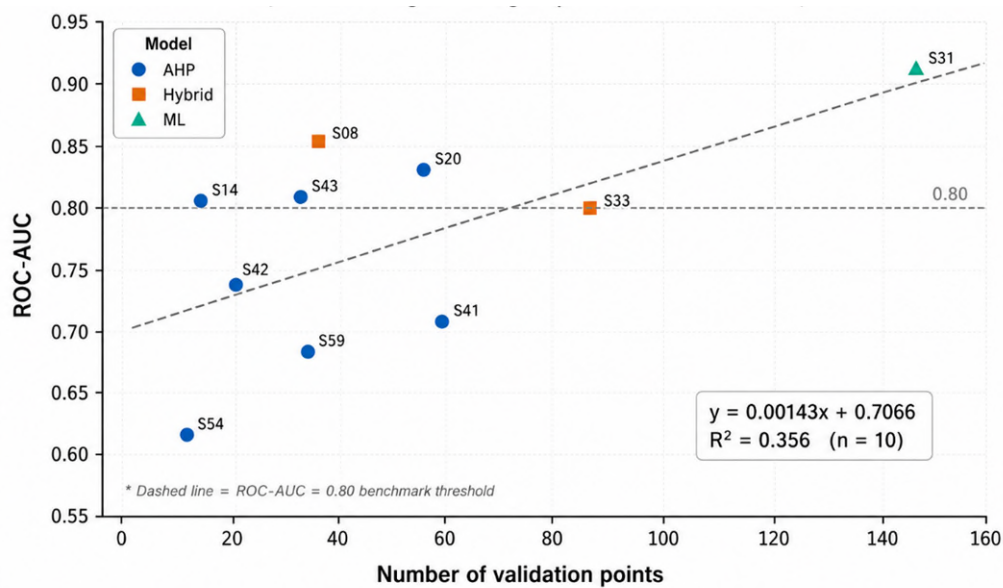


Fig. 9 Regression analysis between field validation point count and ROC-AUC score across geospatial studies (2021–2026). Circle = AHP only; square = AHP-hybrid; triangle = ML/ensemble. Dashed line = linear regression

($y = 0.00145x + 0.702$, $R^2 = 0.394$, $n = 10$). The horizontal dotted line marks the AUC = 0.80 benchmark threshold. Data sources: [08, 14, 20, 31, 33, 41, 42, 43, 54, 59].

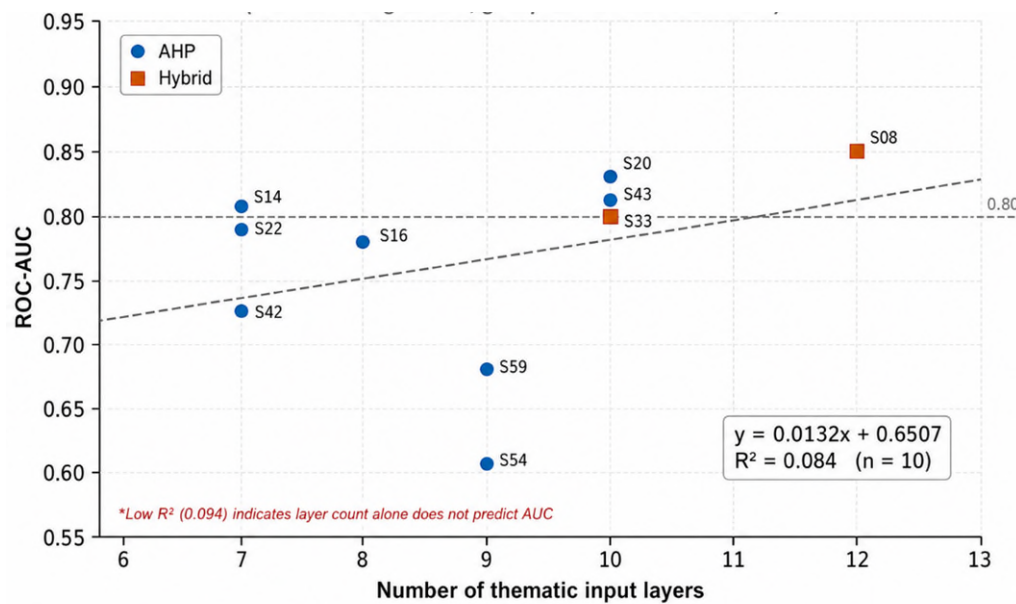


Fig.10 Regression analysis between the number of thematic input layers and ROC-AUC score across 10 AHP-based geospatial studies (2021–2026). The very low R^2 (0.094) indicates that the layer count alone does not predict the model accuracy. $y = 0.0132x + 0.651$. The horizontal dotted line marks the AUC = 0.80 benchmark threshold. Data sources: [08, 14, 16, 20, 22, 33, 42, 43, 54, 59].

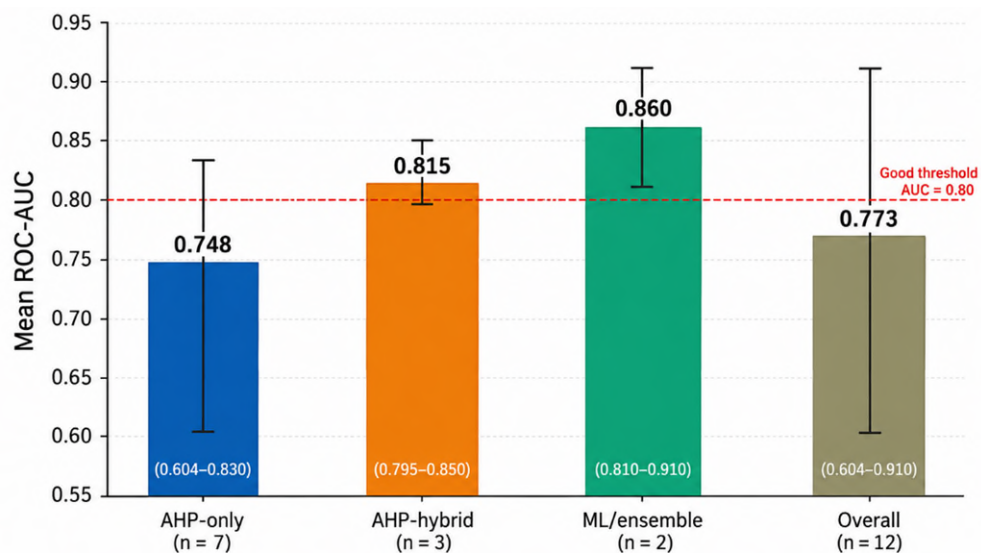


Fig. 11 Mean ROC-AUC by analytical method family across 12 geospatial studies (2021–2026). Error bars represent the minimum-maximum range for each method group. The dashed red line marks the AUC = 0.80 "Good" performance threshold. Numbers above bars indicate mean AUC values; ranges in parentheses below show min-max. AHP = Analytical Hierarchy Process; ML = Machine Learning; RF = Random Forest.

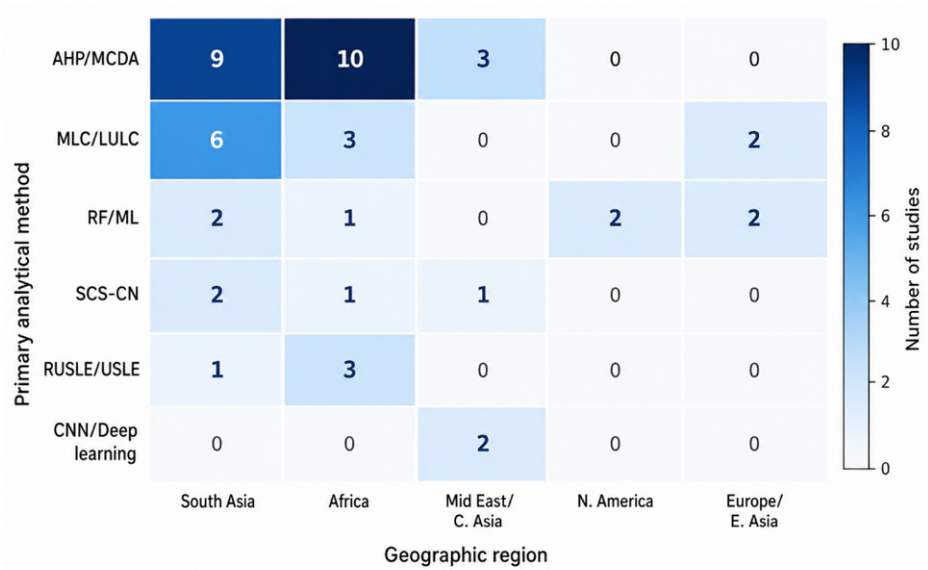


Fig. 12 Heatmap showing the distribution of 59 geospatial studies by primary analytical method and geographic region. The cell values represent the number of studies in each method–region combination. White cells indicate that no studies were identified. The blue intensity increases with the study count (darker shading = higher concentration of studies). Notably, AHP/MCDA is dominant in South Asia and Africa, alongside the near-absence of ML/ensemble methods in these regions.

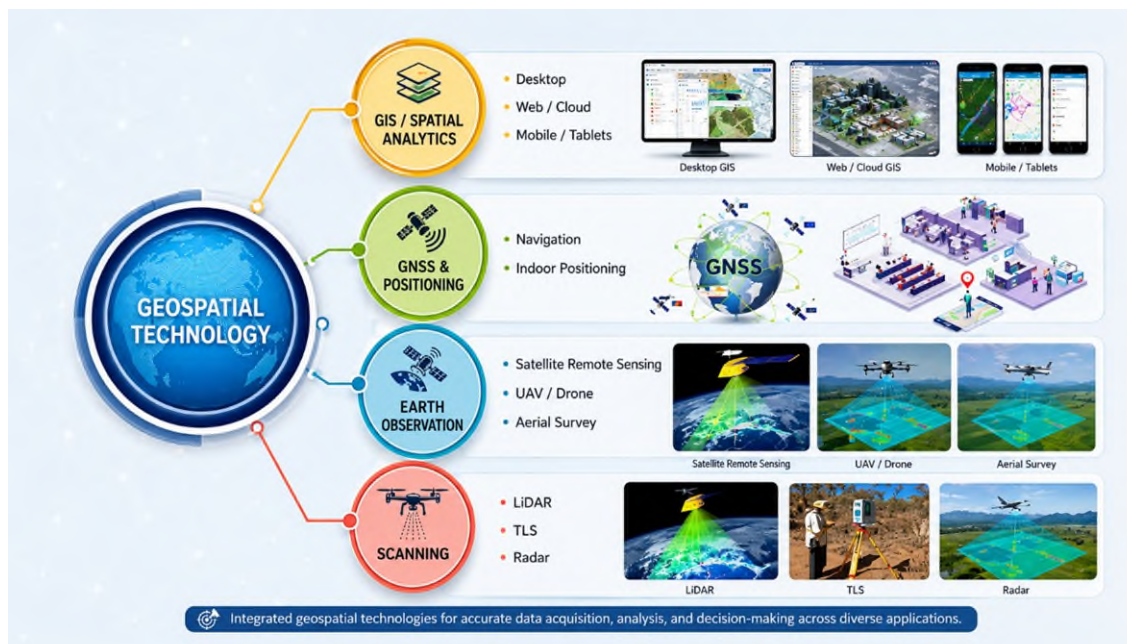


Fig.13 Compound of Geospatial Technology Land and Water Management

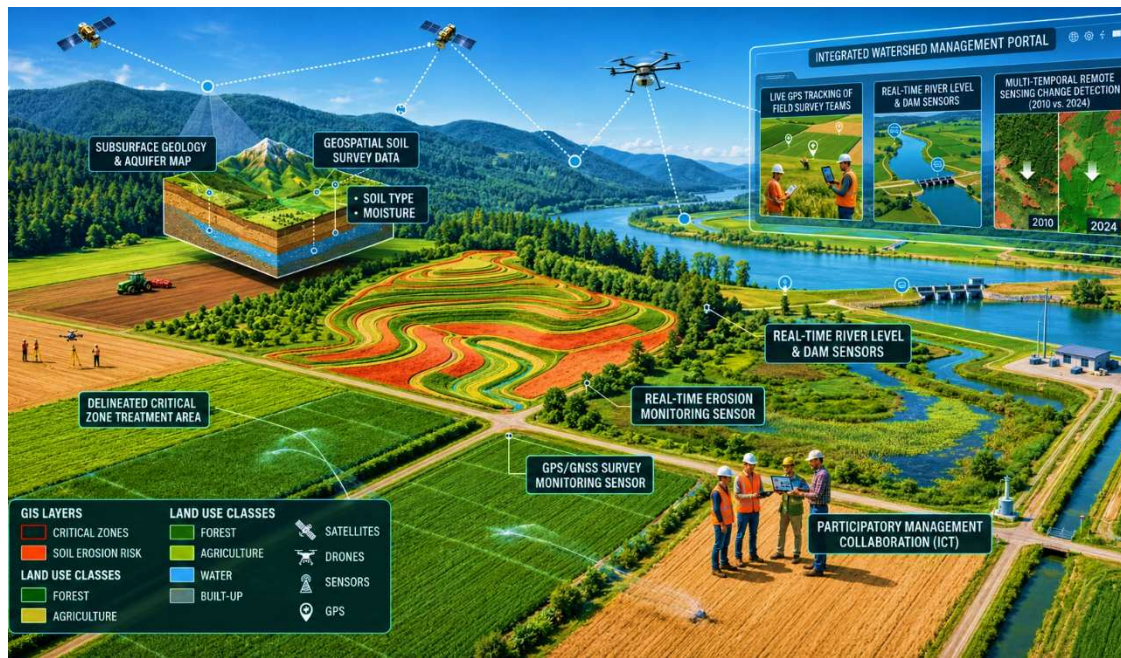


Figure 14 Integrated geospatial technologies (RS, GIS, GPS, UAVs, and IoT) for sustainable watershed management and decision support.

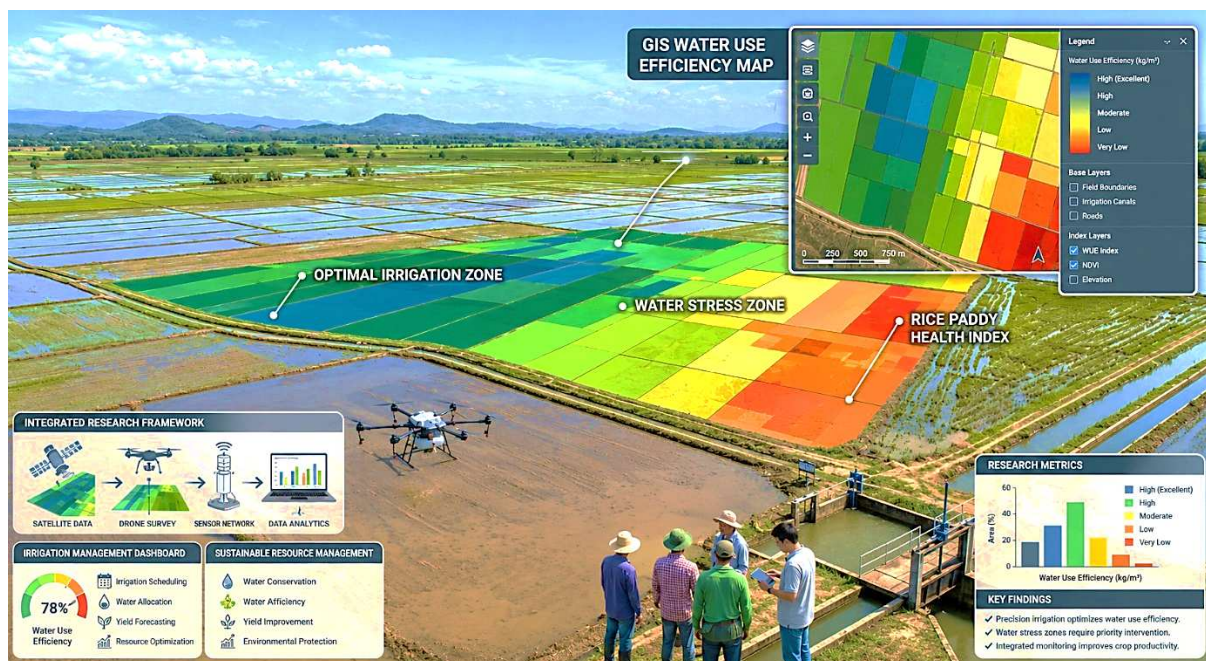


Fig.15 Geospatial-based precision irrigation and crop health assessment using remote sensing, GIS, and UAV technologies.

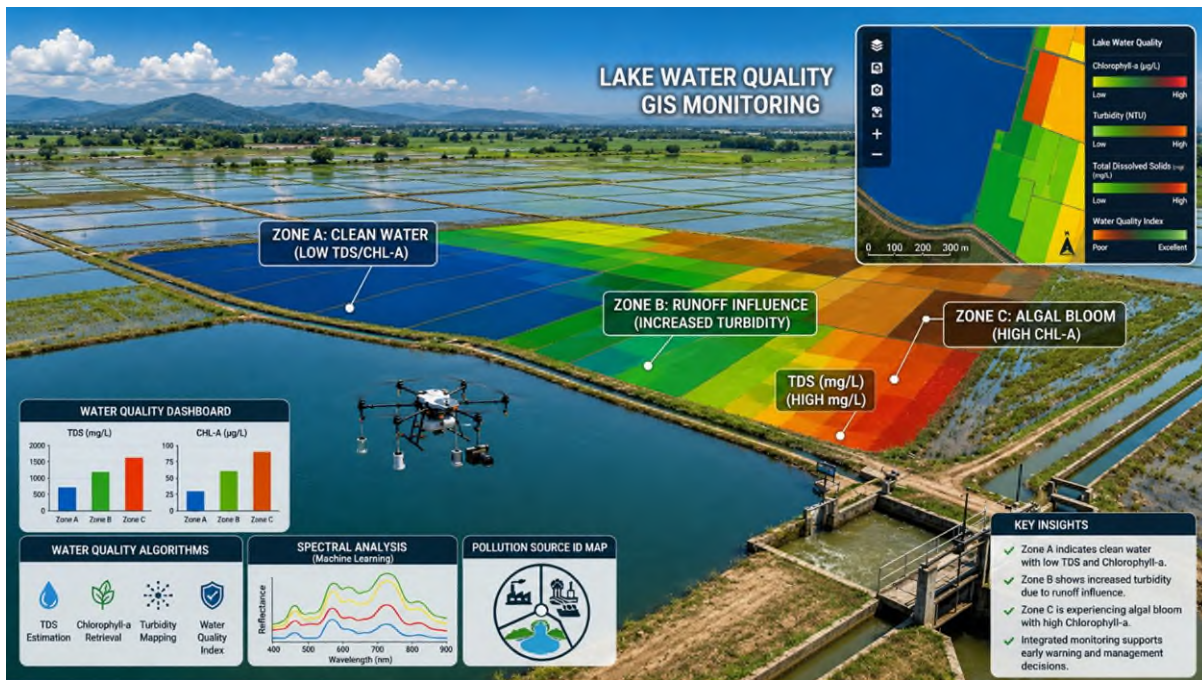


Fig.16 Geospatial-based water quality monitoring and zonation using remote sensing, GIS, and UAV technologies.

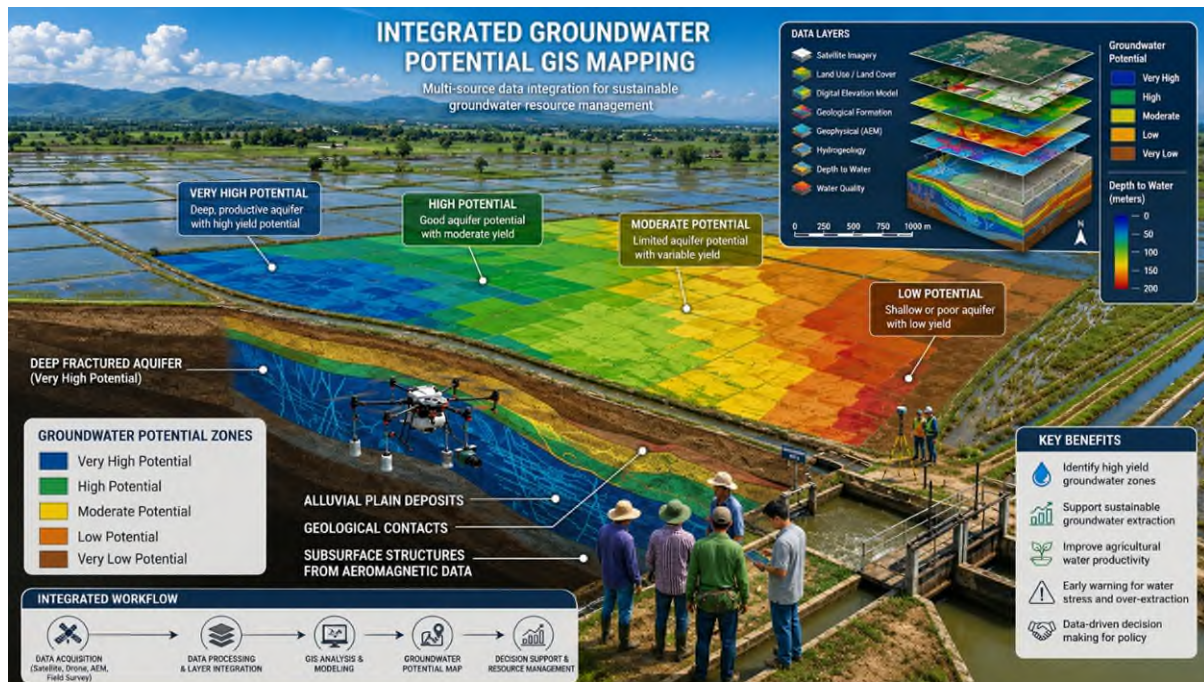


Fig.17 Integrated geospatial approach for groundwater potential mapping using GIS, remote sensing and geophysical data.