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Global trends and gaps in geospatial criteria selection for groundwater and spring water mapping using remote sensing and GIS studies based on multi criteria decision making techniques

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Abstract: Global studies using geospatial methodology on groundwater potential mapping and spring zone assessment provide valuable context for sustainable water resource management through Remote Sensing (RS), Geographic Information Systems (GIS), and Multi-Criteria Decision-Making (MCDM) procedures. The study identifies critical gaps linked to satellite pixel resolution and region-dependent criteria subclass reclassification. A chi-square (χ^2) analysis of 33 criteria derived from total studies on both groundwater ($n = 92$) and spring waters ($n = 58$) resulted in no significant difference ($p > 0.05$), indicating a worldwide reconvergence of parameters including slope, drainage density, lineament density, land use/land cover (LULC), and rainfall. These common parameters operate globally as the principal controls of recharge and water availability. Additional parameters that are driven by the environment and are recognized as region-specific, including geology, geomorphology, soil, and some canopy cover, drive local-scale accuracy. The review also documents a number of less commonly accounted for but important parameters; including curvature, topographic wetness index (TWI), and lithological diversity; that will enhance predictive models under changes to hydro-environmental conditions. Research trends suggest a pronounced increase in publications after 2019, from regions dominated by Asia, including India, Nepal, China, and Ethiopia, through the increased uptake of RS-GIS and machine learning to reach mean accuracies greater than 92%. This study provides new support for the consistency of parameter consideration and indicates previously hidden variables that are important influences, thereby building a scientific rationale for the development of adaptive, automated, and future climate resilient RS-GIS frameworks for future research of groundwater and spring waters.

Key words: Groundwater potential mapping; spring zone identification; water resource planning; remote sensing (RS); geographic information system (GIS); water resource planning.

1. INTRODUCTION

Groundwater is a very important natural resource used for drinking water, farming, and supporting ecosystems. This water scarcity challenge is especially apparent in areas where freshwater resources are limited due to climate change, rapid urbanization, and an increasing population (Baig et al., 2023; Biswas et al., 2012; Brueggen et al., 2010; Kumar, Yadav, et al., 2025; Monem et al., 2014; Rajendrakumar et al., 2025; Sahu et al., 2024; Verma et al., 2025). Global groundwater depletion is a critical issue due to the disparity and overconsumption of groundwater, relative to irrigation, industrial, or other uses (Alemu & Zelalem, 2026; Guduru & Jilo, 2022a). In addition, groundwater characteristics and the techniques used to investigate it vary spatially, and spring water in non-uniform terrain further increases the expense and duration of field surveys, making reliable evaluation more difficult. In the past, traditional groundwater methods like geophysical surveys, test drilling, and field mapping were limited by high costs, long timelines, and localized point data. Modern Remote Sensing and GIS solve these issues by providing cost-effective, rapid, and large-scale spatial data for comprehensive mapping. These modern tools are more affordable, faster, and dependable for finding areas where groundwater is likely to be found i.e. Ground Water Potential Zones (GWPZs) (Attar et al., 2024a; Diriba et al., 2024; Khushi et al., 2023; Kumar Ravi et al., 2023; Ranjan & Kumar, 2020). RS and GIS can combine different types of data such as Geological Parameters, Hydrological Parameters, Soil Parameters, Land Use/Land

Cover Parameters, Meteorological/Climatic Parameters, and Environmental Parameters to identify GWPZs at local to regional scales at both local and larger regional levels (Chohan et al., 2022).

Multi-Criteria Decision-Making (MCDM) techniques, notably Analytic Hierarchy Process (AHP), are being increasingly used to assign weights to influencing factors and improve the accuracy of groundwater mapping. There are many applications of AHP and its variations used to delineate GWPZs in different hydrogeological conditions including hard rock, alluvial plains, karst and mountainous watersheds (Al-Bahrani et al., 2022; Arulbalaji et al., 2019; Doke et al., 2021; Iqbal & Bashir, 2025; Saaty, 2002; Tripathi et al., 2025). More sophisticated techniques such as fuzzy-AHP, Shannon Entropy, Multi-Influence Factor (MIF), as well as Frequency Ratio Models, were compared to AHP to improve decision reliability and minimize subjective bias (Oyda et al., 2025; Tamesgen et al., 2023; Thanh et al., 2022). There is also recent potential with integration of MCDM with machine-learning and probabilistic models for assessing groundwater potential (Acharya & Lee, 2019; Arabameri et al., 2021; Ghosh & Bera, 2024; Jal, 2020; Xu et al., 2022).

Worldwide literature indicates that the environmental factors governing groundwater occurrence and availability vary significantly across different hydrogeological settings. However, certain universal indicators remain consistently linked to groundwater presence, including Lithology, Lineament Density, Slope, Drainage Density, Rainfall/Precipitation, Soil Texture, and Land-Use Land Cover (LULC). In mountainous and hard-rock regions, structural and environmental features like fractures, faults, and geomorphic landforms are dominant controlling factors alongside lithology. Conversely, in areas defined by alluvial parent rocks and sediment basins, recharge conditions from surface hydrology, aquifer characteristics, and soil permeability play a more critical role (Attar et al., 2024a; Bendib et al., 2017; Maqbool et al., 2024; Tamiru & Wagari, 2021). Building on these variations, recent studies from South Asia, Africa, and the Middle East highlight the significant value of integrating hydro-meteorological features and recharge proxies. Characterizing these specific indicators is crucial for accurately delineating springs and groundwater recharge zones, which ultimately forms the foundation for sustainable water resource management (Das & Gupta, 2021; Mathewos et al., 2024; Tabassum et al., 2025; Takele et al., 2025; Thakur et al., 2023).

Recent studies have extensively examined ecosystems at risk from groundwater exploitation, particularly using mountain springs within vulnerable hydrogeological environments. Evidence from regions such as Kashmir, Nepal, Ethiopia, and Morocco reveals that spring occurrences are primarily controlled by litho-structural settings, lineament connectivity, slope breaks, and rainfall recharge combinations (Attar et al., 2024a; El Ayady et al., 2023; Sahoo et al., 2025; Sapkota et al., 2021). Efficiently mapping these spring recharge areas is vital for securing drinking water in rural hill environments and building climate resilience (Charchousi et al., 2025; Elsaidy et al., 2025). To address these variations, this present review systematically analyzes these global criteria trends and methodological approaches across different geographic terrains to improve future spring zone identification.

Validation of groundwater potential models is necessary step to verify their use and utility. There are numerous validation methods reported in the literature through well yield, Receiver Operating Characteristic (ROC) curves or Area Under Curve (AUC) statistics, and success-rate analysis (Bennett, 2024; Brahmanandam & Nagarajan, 2021; Fang et al., 2020; Guduru & Jilo, 2022b). Although the methods verify that thematic layers through GIS and MCDM offer a reliable approach, model effectiveness is significantly determined by appropriate factor selection and assessment of weights. Furthermore, the studies also reiterated the importance of applying sensitivity analysis to address uncertainty in decision-making models (Burayu et al., 2025a; Rahim et al., 2025).

This review seeks to synthesize international geospatial research on groundwater potential mapping with particular attention to the criteria used to delineate spring zones and recharge areas. The objective is to compare several case studies from South Asia, Africa, and beyond, to clarify which criteria are most important, which methods were used, and to highlight the best set of criteria to use for groundwater exploration and planning. Synthesizing groundwater potential mapping studies will not only provide insight to the academic community and scientists on indicators for future groundwater studies, it will also be of practical use to water resource planners, policymakers, and local communities seeking to manage groundwater sustainably(Arya et al., 2025; Kuamar, 2007; A. Kumar, Singh, et al., 2025; Ranjan & Kumar, 2020; Sharma et al., 2024).The use of geospatial techniques facilitates the examination of vast geographical spaces with the same level of importance, particularly where it is not feasible to access the area physically due to difficult terrain. In various hill regions, spring waters are the only sources of groundwater, meaning that site-specific criteria have to be established. As every geographical area has its unique characteristics, an appropriate set of criteria must be developed in order for mapping to be accurate and reliable.

2. METHODOLOGY

The research was designed with a systematic review methodology in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) workflow outlined in Figure 1 (Page et al., 2017; Springer & Stevens, 2009). The PRISMA framework was utilized to ensure transparency, reproducibility, and uniformity in the searching, screening, and inclusion of studies (Díaz-alcaide & Martinez-santos, 2020; Garvin et al., 2017). A multi-faceted search and screening process was conducted to identify the world's geospatial studies associated with Groundwater Potential Mapping (GPM) and criteria associated with Spring Zone Identification. Bibliographic data were exported in RIS format and analysed in VOSviewer (version 1.6.20) to produce keyword co-occurrence maps and clusters (Abdullah et al., 2025; García-Ávila et al., 2023; Pérez-Cutillas et al., 2023; Rajendrakumar et al., 2025).

Data Sources and Search Strategy: Relevant peer-reviewed manuscripts, grey literature, and conference papers were obtained from major scientific databases such as ScienceDirect, ResearcGate and Relevant Journals (Alejano, L.R. and Alonso, 2005; Díaz-Alcaide & Martínez-Santos, 2019; Mohapatra et al., 2025). The search inclusive key words were related to the Groundwater, Spring water studies based on Remote Sensing and GIS integrated with MCDM and ML techniques. The literature timeframe considered numbers spanning during 2000–2025, to ensure both classic and contemporary documents were included in groundwater potential and spring zone mapping (Abdullah et al., 2025; Abijith et al., 2020; Burayu et al., 2025b; Mallik et al., 2021; Park, 2010; Poudel et al., 2024; Rahman et al., 2022; Saaty, 2002; Saaty & Hall, 2012; Tamesgen et al., 2023; Yifru et al., 2020).

Screening and Eligibility: The review process adhered to a systematic approach guided by PRISMA. Initially, records were filtered at the title and abstract level for relevance to groundwater potential mapping, based on either the absence of geospatial methods or clearly identified criteria for spring/groundwater identified (Elsaidy et al., 2025; Garvin et al., 2017; Page et al., 2017). Duplicate records were subsequently removed, with high-quality reviews of the eligible studies' full texts. The relevant studies are identified after multiple triangulations.

AHP Integration: The Analytical Hierarchy Process (AHP) framework is employed in this study to analyze the criterion weights. Judgments obtained from three hydrogeological experts were used to manually fill in the pair-wise comparison matrices. Tabulated data is transformed to numeric values using the arithmetic averaging method in order to standardize them in single values. A consistency ratio is also calculated to ensure the under (<0.1) for validity of the above step.

Statistical Analysis: Chi-square (χ^2) tests of independence were performed to compare the frequency of selected geospatial criteria between Groundwater ($n = 92$) and Spring water ($n = 58$) studies. Statistical significance was assessed at $\alpha = 0.05$. Model performance was evaluated using Receiver Operating Characteristic (ROC) analysis and the Area Under the Curve (AUC).

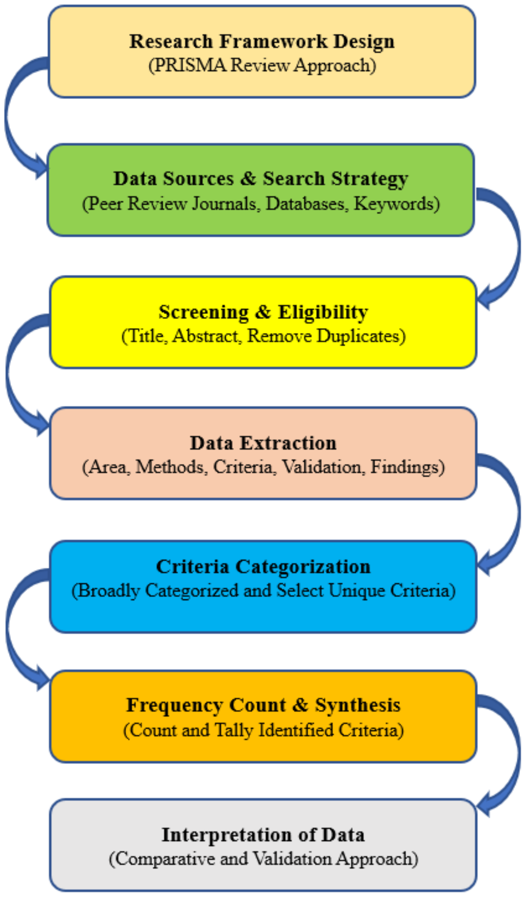

Figure 1. A study design for review of global studies (PRISMA approach)

2.1 Data extraction and criteria categorization

Data were meticulously gathered based on the study area, method (RS, GIS, MCDM, ML, or hybrid study method), criteria (e.g., Lithology, Slope, Drainage Density, Rainfall, LULC), validation (e.g., ROC–AUC, Well-Yield Testing), and overall conclusions (Attar et al., 2024a; Elubid et al., 2020; M. Kumar et al., 2022; Tamiru & Wagari, 2021). Criteria were synthesized into thematic unique classes while unthematic criteria as Human Activities (e.g., Industrial Groundwater Use), Social Pressure (e.g., Population Density, Tourism Places), and groundwater composition factors (e.g., Total Dissolved Solids) were broadly synthesized in simple categories: Anthropogenic Activity, Community Factors, Evapotranspiration, Hydrochemistry, Natural Hazards, Vegetation, and Water Quality Parameters.

2.2 Frequency count and synthesis

The frequency counter method was used to tally one or more parameters that had consistently been identified in studies, across globally-based studies. Groundwater and spring-based studies were tallied independently with a collective count to rank global ranking factors. Several Rare but emerging parameters (e.g., Soil Moisture, Hydrochemistry, Land Surface Temperature and Hillshade etc.) were also noted (Bendib et al., 2017; M. Kumar et al., 2022; Nsangou et al., 2022). The applicable, statistical measures (i.e., Chi-Square test, p-values) were used to determine significance factor selection. A comparative synthesis of studies practiced methodology, validation methods and possible advances in future studies was reference.

3. RESULTS AND DISCUSSION

In this study, individual Chi-square (χ^2) tests of independence were performed to systematically compare the selection frequency of each of the 33 criteria between Groundwater (n=92) and Spring water studies (n=58). For each criterion, a (2×2) contingency table (representing study type vs. presence/absence of the criterion) was utilized to calculate the (χ^2) statistic based on observed versus expected frequencies. A significance threshold of ($\alpha = 0.05$) was set for results interpretation. Overall, the research shows that water resources assessments lean towards a standardized core of universal criteria with specific parameters varying according to context. Thus, both standardization and contextual adaptability are maintained in water resources assessments across groundwater and spring water researchers.

As presented in Table 1, all evaluated criteria yielded a ($p > 0.05$), demonstrating that the variations in criteria usage between groundwater and spring studies are not statistically significant. This confirms that both fields rely on a highly consistent and standardized core of Remote Sensing and GIS-based parameters (Elsaidy et al., 2025; Kurzweil et al., 2021; Saaty, 2002). Specifically, Slope (Rank 1, 68.7%), Drainage Density (Rank 2, 62.0%), Lineament Density (Rank 3, 57.3%), LULC (Rank 4, 56.7%), and Rainfall (Rank 5, 53.3%) emerge as the universally accepted controlling factors, with each appearing in over 50 percent of the reviewed literature. These are followed by moderately accepted features like Soil (42.7%), Geology (41.3%), and Lithology (39.3%) that account for subsurface characteristics (Daniel et al., 2021; M. Kumar et al., 2022; Liu et al., 2025; Ranjan & Kumar, 2020). Conversely, highly specialized criteria like Soil Moisture (2.0%) and Hillshade (1.3%) showed low global applicability, reflecting their discretionary use based on local geographic settings.

While the comparative chi-square analysis indicates that groundwater and spring studies draw on a largely identical set of Remote Sensing & GIS criteria, the absolute number of groundwater investigations is much higher than spring-focused mapping. It is completely understandable that groundwater studies dominate the literature, given that springs represent a specific subset of broader Groundwater Dependent Ecosystems (GDEs). However, evaluating this imbalance highlights a clear gap in literature: while geospatial frameworks for groundwater potential mapping have reached methodological maturity, their direct translation into localized spring-water management remains significantly underexplored. Because springs serve as vital drinking water sources in complex mountain terrains, adapting these mature frameworks can directly improve targeted spring-shed planning, ensuring water security for marginalized rural communities and supporting localized ecological conservation.

The illustration displays in Figure 2 the frequency and ranks of 33 criteria utilized in a suite of combined groundwater and spring studies. Eight natural criteria - Slope, Drainage Density, Lineament Density, LULC, Rainfall, Geomorphology, Soil, and Geology - were identified as having the highest frequencies and ranks, thus further establishing their importance in groundwater mapping. The next level of prominence is found in Lithology, Elevation, Groundwater Depth, and TWI. Criteria such as Soil Moisture, Hydrochemistry, LST, and Hillshade were still observed in a portion of the studies, showing less frequency and rank but signaling an emerging interest (Jung et al., 2024; A. Kumar, Singh, et al., 2025; R. Verma & Jamwal, 2022). Given that almost all frequency and rank scores for all criteria reflect a clear predominance of physiographic and hydro-geological criteria relative to the use of anthropogenic and environmental factors (limited as it may be), this analysis demonstrates an established framework with limited, but emerging, interest in anthropogenic and environmental criteria.

In the Figure 3 exclusive groundwater-related investigations, the three criteria of slope, lineament density, and drainage density were identified as paramount criteria, indicative of their primacy (Attar et al., 2024b; A. Kumar, Singh, et al., 2025; Taloor et al., 2022). The lithology and the rainfall criteria were relatively high among the five ranking lists, indicating they remain important. Conversely, criteria such as soil moisture, vegetation, and hydrochemistry were lower ranked; while these parameters are common in identifying Groundwater Dependent Ecosystems (GDEs), their low global application frequency highlights an opportunity for more consistent integration in future localized mapping.

Table 1. Comparative frequency of criteria selection in groundwater vs. spring studies

S. No.	Criteria	GW Studies (n=92)	Spring Studies (n=58)	Combined (n=150)	χ^2 Value	p-value	Rank	Category
1	Anthropogenic Activity	12 (13.0%)	7 (12.1%)	19 (12.7%)	0.021	0.885	14	Human Impact
2	Aquifer Properties	5 (5.4%)	3 (5.2%)	8 (5.3%)	0.002	0.963	19	Hydrogeological
3	Aspect	4 (4.3%)	3 (5.2%)	7 (4.7%)	0.074	0.785	20	Topographic
4	Climate	11 (12.0%)	7 (12.1%)	18 (12.0%)	0.000	0.989	15	Climatic
5	Community Factors	5 (5.4%)	3 (5.2%)	8 (5.3%)	0.002	0.963	19	Social
6	Curvature	7 (7.6%)	4 (6.9%)	11 (7.3%)	0.041	0.839	17	Topographic
7	Drainage Density	57 (62.0%)	36 (62.1%)	93 (62.0%)	0.000	0.989	2	Hydrological
8	Elevation	27 (29.3%)	17 (29.3%)	44 (29.3%)	0.000	0.995	10	Topographic
9	Evapotranspiration	6 (6.5%)	4 (6.9%)	10 (6.7%)	0.006	0.939	18	Climatic
10	Flow Direction	5 (5.4%)	3 (5.2%)	8 (5.3%)	0.002	0.963	19	Hydrological
11	Geology	37 (40.2%)	25 (43.1%)	62 (41.3%)	0.118	0.731	8	Geological
12	Geomorphology	40 (43.5%)	27 (46.6%)	67 (44.7%)	0.133	0.715	6	Geo-Morphological
13	Groundwater Depth	16 (17.4%)	11 (19.0%)	27 (18.0%)	0.058	0.810	11	Hydro-Geological
14	Hillshade	1 (1.1%)	1 (1.7%)	2 (1.3%)	0.084	0.772	24	Topographic
15	Hydrochemistry	3 (3.3%)	2 (3.4%)	5 (3.3%)	0.001	0.981	21	Chemical
16	Irrigation	6 (6.5%)	4 (6.9%)	10 (6.7%)	0.006	0.939	18	Human Impact
17	Lineament Density	53 (57.6%)	33 (56.9%)	86 (57.3%)	0.007	0.932	3	Environmental
18	Lithology	36 (39.1%)	23 (39.7%)	59 (39.3%)	0.005	0.944	9	Environmental
19	LST	3 (3.3%)	2 (3.4%)	5 (3.3%)	0.001	0.981	21	Structural
20	LULC	52 (56.5%)	33 (56.9%)	85 (56.7%)	0.002	0.964	4	Geological
21	Natural Hazards	4 (4.3%)	3 (5.2%)	7 (4.7%)	0.074	0.785	20	Risk
22	Proximity to Water	10 (10.9%)	6 (10.3%)	16 (10.7%)	0.006	0.941	16	Spatial
23	Rainfall	49 (53.3%)	31 (53.4%)	80 (53.3%)	0.001	0.982	5	Climatic
24	Roughness	4 (4.3%)	3 (5.2%)	7 (4.7%)	0.074	0.785	20	Topographic
25	Slope	63 (68.5%)	40 (69.0%)	103 (68.7%)	0.004	0.950	1	Topographic
26	Soil	39 (42.4%)	25 (43.1%)	64 (42.7%)	0.006	0.940	7	Pedological
27	Soil Moisture	2 (2.2%)	1 (1.7%)	3 (2.0%)	0.056	0.813	23	Environmental
28	Spring/Well Discharge	16 (17.4%)	10 (17.2%)	26 (17.3%)	0.001	0.976	12	Hydrological
29	Stream Order	2 (2.2%)	1 (1.7%)	3 (2.0%)	0.056	0.813	22	Hydrological
30	TPI	5 (5.4%)	3 (5.2%)	8 (5.3%)	0.002	0.963	19	Topographic
31	TWI	13 (14.1%)	8 (13.8%)	21 (14.0%)	0.002	0.963	13	Topographic
32	Vegetation	13 (14.1%)	8 (13.8%)	21 (14.0%)	0.002	0.963	13	Environmental
33	Water Quality	11 (12.0%)	7 (12.1%)	18 (12.0%)	0.000	0.989	15	Chemical

According to Figure 4, drainage density, rainfall, slope, and lithology are the four most frequently selected spring study criteria, which clearly identifies these factors as being more significant in determining spring location and discharge (Ameen, 2019; Daniel et al., 2021). In contrast geomorphology, irrigation, and aquifer parameters were less frequently included, suggesting gaps and opportunities for research on integrating these parameters into future studies. Overall, the trend suggests a stronger reliance on hydrologic and terrain variables than socio-environmental indicators.

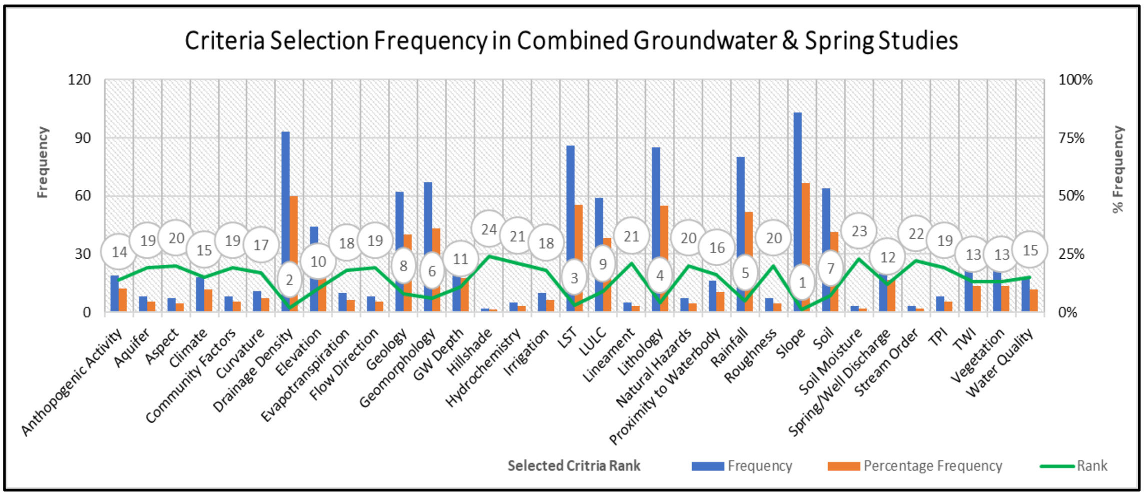

Figure 2. Selected criteria frequency and rank in combined GW & spring studies

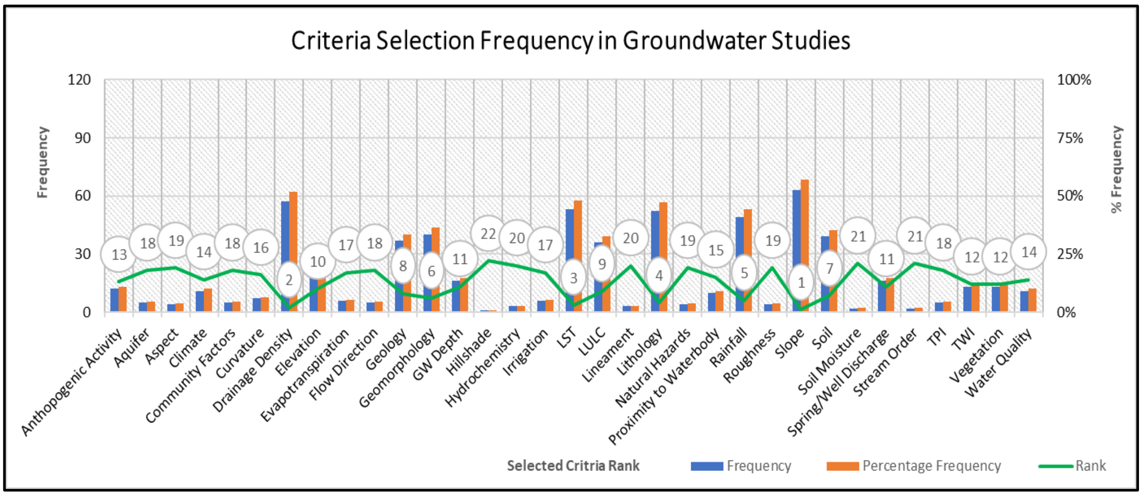

Figure 3. Selected criteria frequency and rank in GW studies

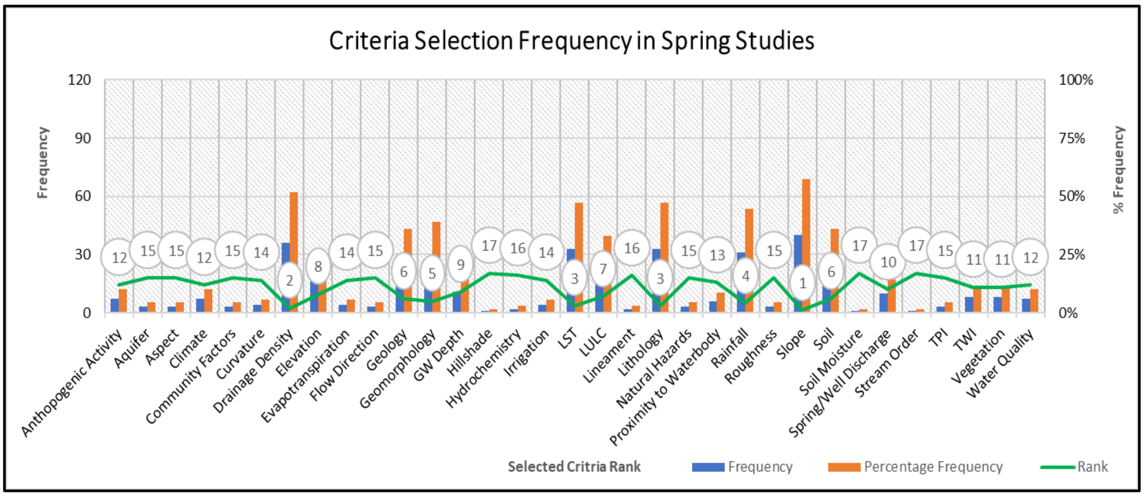

Figure 4. Selected criteria frequency and rank in spring studies

The breakdown of study frequency by country, Table 2 indicates that India accounts for the largest proportion of studies (42.68%) with relatively even representation between groundwater (33.70%) and spring studies (39.66%). Ethiopia (18.48% of groundwater studies) and China (5.10% total) also contribute significantly; however, Nepal has the most with spring-related studies

(10.34%). Other countries like Pakistan, Egypt, Iran, and the USA show moderate representation. Brazil, Japan, Jordan, and Morocco feature only some isolated cases of studies. About 9.55% of the studies cite global reviews, representing a synthesis across regions (Diriba et al., 2024; Mussa et al., 2024; Park, 2010, 2010; Yifru et al., 2020).

Table 2. Country wise study frequency distribution in GW and spring studies

Country Name	Total Studies	Total Studies Frequency (%)	Groundwater Studies	Groundwater Studies Frequency (%)	Spring Studies	Spring Studies Frequency (%)
Brazil	1	0.64%	0	0.00%	1	1.72%
China	8	5.10%	5	5.43%	2	3.45%
Egypt	2	1.27%	2	2.17%	0	0.00%
Ethiopia	17	10.83%	17	18.48%	0	0.00%
Global	15	9.55%	7	7.61%	2	3.45%
India	67	42.68%	31	33.70%	23	39.66%
Indonesia	1	0.64%	1	1.09%	0	0.00%
Iran	3	1.91%	3	3.26%	0	0.00%
Iraq	2	1.27%	2	2.17%	0	0.00%
Japan	1	0.64%	0	0.00%	1	1.72%
Jordan	1	0.64%	0	0.00%	1	1.72%
Mexico	2	1.27%	0	0.00%	2	3.45%
Morocco	2	1.27%	1	1.09%	1	1.72%
Nepal	8	5.10%	2	2.17%	6	10.34%
Nigeria	3	1.91%	2	2.17%	1	1.72%
Pakistan	5	3.18%	4	4.35%	1	1.72%
Poland	1	0.64%	0	0.00%	1	1.72%
Regional	2	1.27%	2	2.17%	0	0.00%
Saudi Arabia	1	0.64%	1	1.09%	0	0.00%
South Africa	1	0.64%	1	1.09%	0	0.00%
Thailand	1	0.64%	1	1.09%	0	0.00%
Turkey	1	0.64%	1	1.09%	0	0.00%
United Kingdom	1	0.64%	1	1.09%	0	0.00%
USA	4	2.55%	1	1.09%	3	5.17%
Unspecified	6	3.82%	6	6.52%	0	0.00%
Zimbabwe	1	0.64%	1	1.09%	0	0.00%
Total	**157**	**100%**	**92**	**100%**	**58**	**100%**

Figure 5 presents the aggregated distribution of groundwater and spring studies as a heat map, with Asia as the global research hub, especially India, Nepal, China, and Ethiopia being the focus. Figure 6 shows Asia represents a large proportion of overall studies more strongly in groundwater research, and Figure 7 presents a similar trend in the distribution of spring studies, with even more focus in the Himalayan and mountainous regions (Nisa & Umar, 2024; Sahoo et al., 2025; Sahu et al., 2024). The trend from figures 5-7 represents the importance and ease of studying groundwater and springs for Asia, along with the complexity of themes being identified across the research. This spatial clustering of research effort in Asia highlights both the acute groundwater and spring-water pressures in these regions and the availability of detailed geospatial datasets to investigate them. Consequently, insights from Asian case studies provide a methodological benchmark and transferable lessons for applying RS–GIS based criteria selection in other data-scarce yet hydrogeologically complex parts of the world.

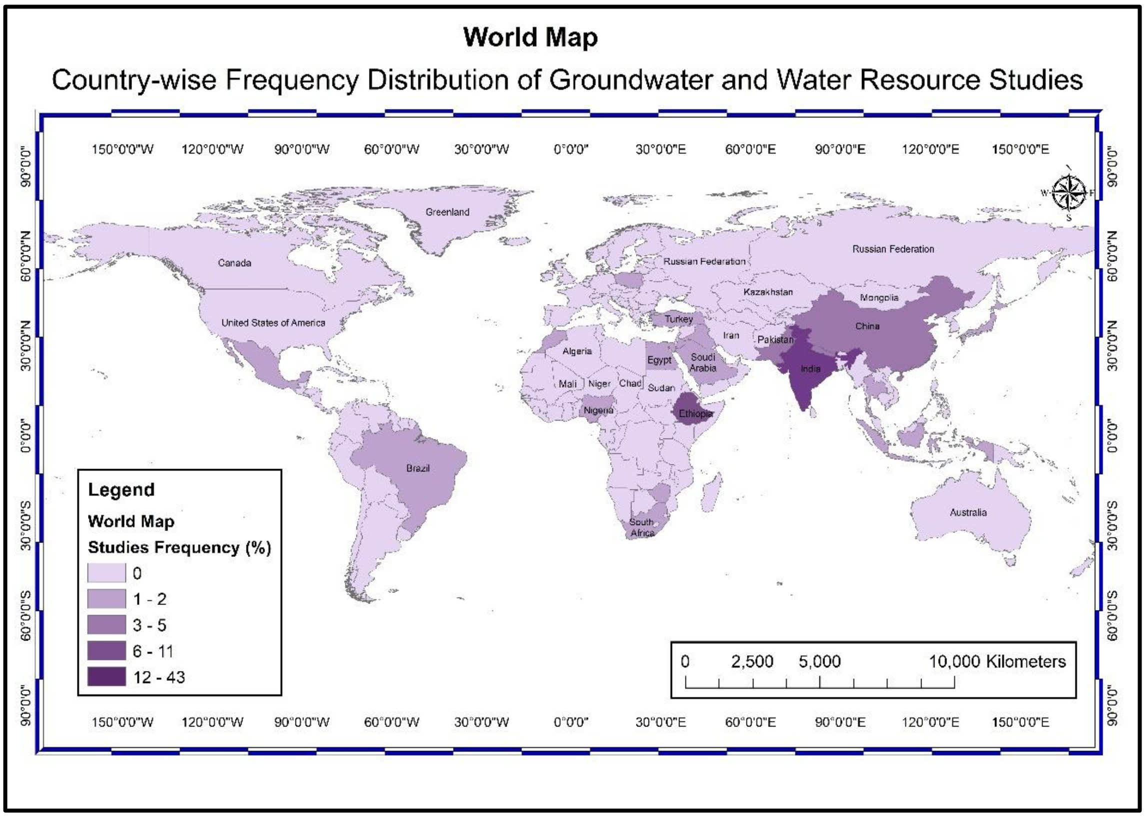

Figure 5. Country wise study frequency distribution in GW and spring studies

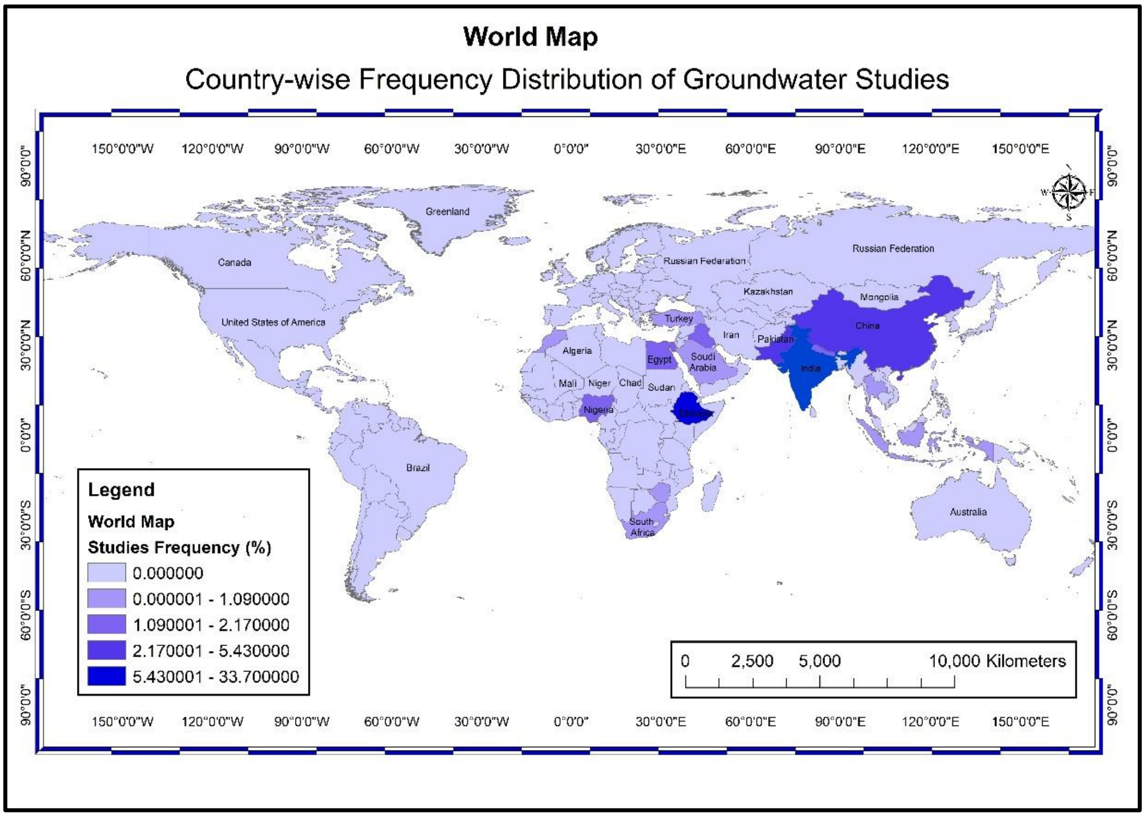

Figure 6. Country wise study frequency distribution in GW studies

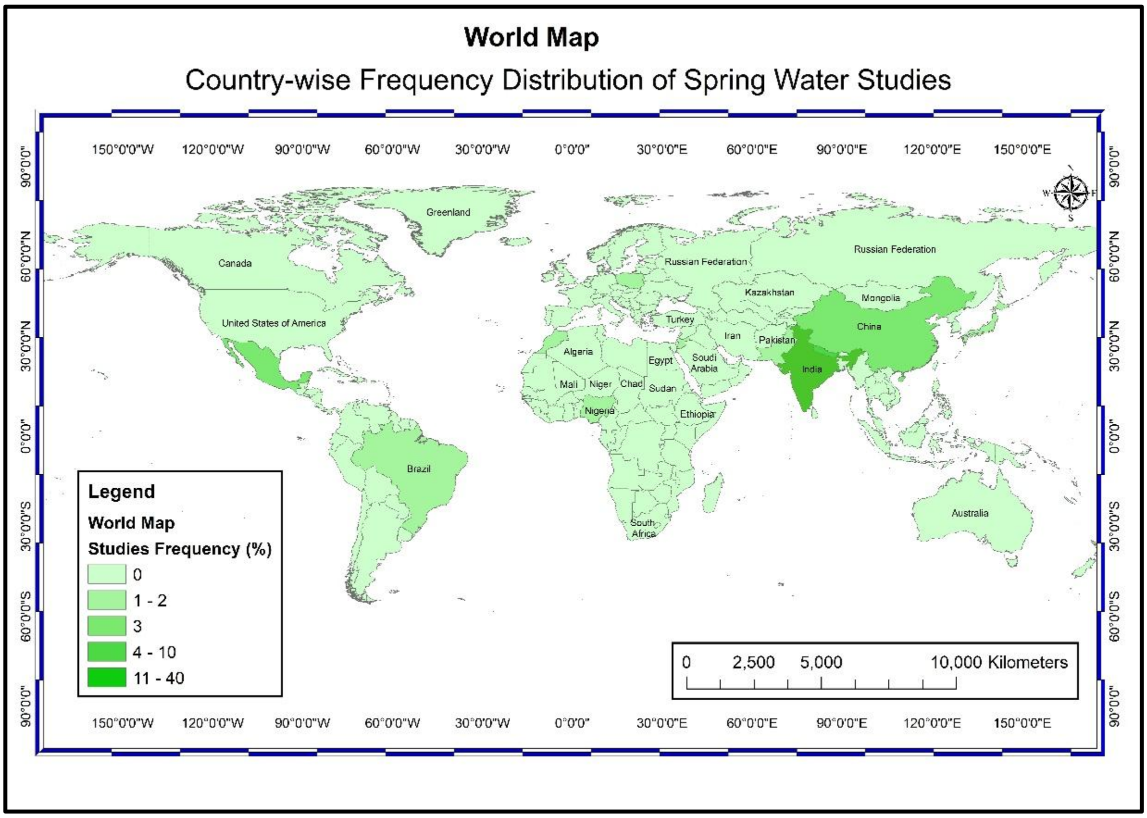

Figure 7. Country wise study frequency distribution in spring studies

In Table 3 data collected regarding springs and groundwater from 2000 to 2025 show in Figure 8, a slow productivity of research output until 2015, a period of plateau rates of research from 2016 to 2018, and then a distinct jump in the productivity of research output post-2019 (Adeyeye et al., 2019; Al-Najjar & Pradhan, 2021; Arabameri et al., 2021; Arshad et al., 2020; Bi et al., 2024; Sorensen et al., 2016). The total number of research peaked in 2024 with 33 papers published, reflecting a greater global interest in assessments of water resources. Groundwater research (92; 61.3%) accounts for the bulk of research output in the overall timeframe while spring research (58; 38.7%) appeared to undergo a lagged but substantial increase, particularly in 2023 which garnered its greatest share of the total output (20.7% of annual publications).

Table 3. Temporal distribution of GW and spring studies during 2000-2025

Year	Total Studies	Total Studies Frequency (%)	Groundwater Studies	Groundwater Studies Frequency (%)	Spring Studies	Spring Studies Frequency (%)
2000	2	1.33	1	1.09	1	1.72
2004	1	0.67	0	0.00	1	1.72
2011	1	0.67	0	0.00	1	1.72
2012	0	0.00	0	0.00	0	0.00
2013	4	2.67	2	2.17	2	3.45
2014	1	0.67	0	0.00	1	1.72
2015	2	1.33	2	2.17	0	0.00
2017	5	3.33	2	2.17	3	5.17
2018	3	2.00	2	2.17	1	1.72
2019	8	5.33	6	6.52	2	3.45
2020	16	10.67	10	10.87	6	10.34
2021	16	10.67	10	10.87	6	10.34
2022	19	12.67	12	13.04	7	12.07
2023	18	12.00	6	6.52	12	20.69
2024	33	22.00	22	23.91	11	18.97
2025	21	14.00	17	18.48	4	6.90
Total Study	**150**	**100.00**	**92**	**100.00**	**58**	**100.00**

Research output on groundwater increased in a more constant pattern, whereas springs research output was variable overall, showing a decrease in research output on springs in 2025 after an increase in springs research output from 2020 to 2022. This spread of phase highlights methodological and technological advancements - namely growing reliance on RS-GIS and machine learning - that have enabled more focused research on groundwater and spring processes in the last few years. More broadly, this pattern recognizes groundwater as a growing global resource and, emerging yet unstated interest in spring ecosystems.

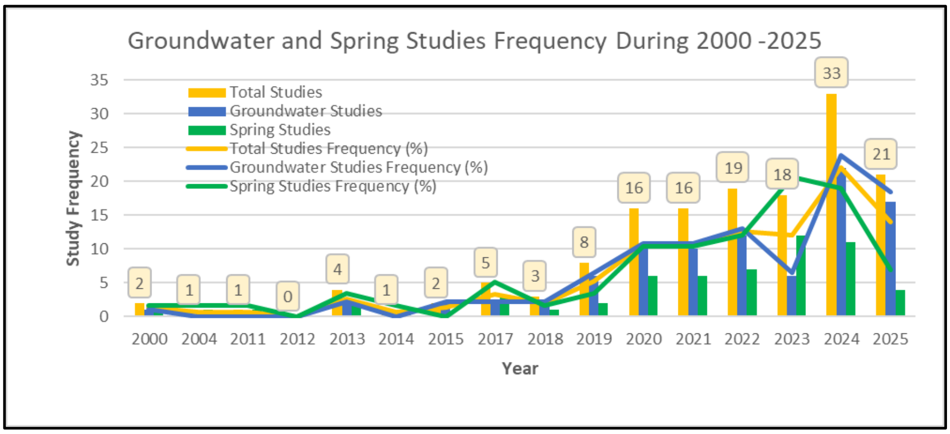

Figure 8. Groundwater and spring studies frequency during 2000 -2025

In the Table 4 comparison, the prediction accuracy for mapping groundwater and spring water potential zones clearly diverges across the three method categories. Traditional Methods (n=21) show the lowest mean accuracy (76.8%, SD = 9.2) and lower ROC-AUC ranges (0.65–0.82), highlighting their limitations in capturing complex spatial data. In contrast, RS-GIS Integration (n=81) significantly improves performance with a higher mean accuracy of 84.6% (ROC-AUC: 0.73–0.92). The highest performance is achieved by Advanced RS-GIS+ML approaches (n=46), reaching a mean accuracy of 92.3% and a superior ROC-AUC range of 0.85–0.98. Across all these reviewed studies, this accuracy measures how well each model predicts actual water zones, validated primarily through Receiver Operating Characteristic (ROC-AUC) Area Under Curves and field verification data (Anh et al., 2023; Pant et al., 2024; Parihar et al., 2021).

RS-GIS (n=81) significantly improved accuracy to a mean of 84.6% (SD=7.4), and tighter confidence interval (83.0–86.2%). The median accuracy reported of 85.0% and the narrower ROC-AUC range (0.73-0.92) demonstrate the strengths of being able to handle spatial data and represent heterogeneous hydrological and geological conditions (Charchousi et al., 2025; Dhakal et al., 2024).

Advanced RS-GIS and machine learning (n=46) provided the highest performance mean accuracy: 92.3% (SD = 4.8), and consistent performance (82-98%). The confidence interval was narrow (90.5-94.1) and the ROC-AUC was even higher (0.85-0.98). This clearly supports the advantages of hybrid approaches in typically demonstrating the highest pattern recognition, the capacity to merge features and represent predictive reliability (Arabameri et al., 2021; Ghosh & Bera, 2024; Pourhashemi et al., 2025; Xu et al., 2022). This demonstrates that the integration of a machine learning approach significantly enhances accuracy and model generalizability beyond traditional and RS-GIS stand-alone methods.

Table 4. Accuracy analysis by methodology

Method Category	Studies (n)	Mean Accuracy (%)	SD	Min-Max	95% CI	Median	ROC-AUC
Traditional Methods	21	76.8	9.2	60-89	72.9-80.7	77.0	0.65-0.82
RS-GIS Integration	81	84.6	7.4	68-96	83.0-86.2	85.0	0.73-0.92
Advanced RS-GIS+ML	46	92.3	4.8	82-98	90.5-94.1	93.0	0.85-0.98

In the Table 5 indicates that machine learning algorithm performance in groundwater and spring studies (2019–2025) suggests tradeoffs of accuracy, efficiency, and computational cost. Random Forest had the highest application number, with n = 18, mean accuracy, 91.8% (SD = 3.2), fast processing, and relatively moderate costs, thus indicating it is suitable for general mapping. Tree-based approaches offered higher accuracy in general (Random Forest, XGBoost, and Ensemble methods), while kernel-based support vector machine (SVM) models and neural-network (ANN/MLP) models were strong performers in more complex terrains and more overtly non-linear conditions, but had more computational cost associated with them.

Conversely, XGBoost (n=8) and Ensemble Methods (n=4) provided better predictive performance, with mean accuracies of 94.1% and 95.2%, respectively. However, both methods have higher resource costs, especially Ensemble Methods that are best fit when maximizing reliability is more important than efficiency in critical applications.

Comparatively, while SVM meant accuracy was only (87.4%), slower processing meant it is less useful, although may still have value in mapping of complex terrain due to the high-dimensional feature space capabilities. Further, ANN/MLP (n=9) achieved a relatively high accuracy (92.6%) but high-cost computationally and longer processing times, which presents limitations and utility mainly in non-linear systems where no other models are deemed better (Ghosh & Bera, 2024; Mussa et al., 2024; Xu et al., 2022).

Thus, while Ensemble and boosting-based models generated the greatest accuracies, Random Forest is still functioning best in a balanced manner for accuracy, efficiency, and scalability, justifying its predominance in the studies published in recent years related to groundwater and springs.

Table 5. Machine learning algorithm performance (2019-2025 studies)

Algorithm	Frequency	Mean Accuracy (%)	SD	Min-Max	Processing Time	Computational Cost	Best Use Case
Random Forest	18	91.8	3.2	85-97	Fast	Medium	General mapping
XGBoost	8	94.1	2.7	89-98	Medium	High	Large datasets
SVM	9	87.4	4.8	78-94	Slow	High	Complex terrain
ANN/MLP	7	92.6	3.9	86-98	Very Slow	Very High	Non-linear relations
Ensemble Methods	4	95.2	1.8	93-98	Very Slow	Very High	Critical applications

SVM- Support Vector Machine, ANN- Artificial Neural Network, MLP- Multilayer Perceptron

According to Table 6, methods of validation greatly differ in use, reliability, and expense. Well yield data (59.3%) was the most widely used method, with good overall reliability (9.2/10) in addition to a reasonable expense. Pumping tests and geophysical methods, although used rarely, conducted dual-credibility tests, however, they were also the most expensive method, so appropriate if testing involved a critical issue. Field verification and the ROC-AUC, was also commonly used (52%). Both of these tests were reliable and less expensive than the testing previously mentioned, such as pumping tests. Expert opinion was free, however, rated low in reliability (6.5/10), which could indicate that while it may complement findings from empirical studies, it should not substitute for objective validation.

Table 6. Validation method frequency and reliability

`	Frequency	Percentage	Reliability Score*	Mean Accuracy (%)	SD	Cost Factor
Well Yield Data	89	59.3%	9.2	85.6	7.2	Medium
Spring Discharge	26	17.3%	8.7	84.3	6.8	Medium
ROC-AUC Analysis	78	52.0%	8.8	87.2	5.9	Low
Pumping Test Data	34	22.7%	9.4	89.1	4.2	Very High
Field Verification / Field Survey	78	52.0%	9.2	86.8	6.4	High
Statistical Cross-Validation	34	22.7%	8.5	88.9	4.8	Low
Expert Opinion	12	8.0%	6.5	79.1	5.0	–
Geophysical Methods	18	12.0%	8.9	87.4	5.5	Very High

*Reliability scores out of 10 based on literature consensus

Table 7 provides inter-criteria influence matrix resulting from expert judgments based on the Analytic Hierarchy Process (AHP) that indicate the relative strength of interaction among ten important parameters that influence groundwater and spring potential. Slope has strong relationships with TWI (0.68), Elevation (0.75), and Geomorphology (0.70) and is therefore an important factor that impacts water flow at the surface and shallow subsurface. Drainage Density has strong interactions with Rainfall (0.72) and TWI (0.78), indicating that surface runoff and catchment features are important to the potential for groundwater recharge. Lineament Density has strong interactions with Geology (0.85) and Geomorphology (0.75), demonstrating the structural control of groundwater flow direction. LULC has moderate interactions with Slope (0.65) and Soil (0.65) and Rainfall has a moderate to strong connection with TWI (0.70) and Geomorphology (0.62). Geomorphology, Soil, Geology, Elevation, and TWI feature multiple strong or moderate interactions among their own parameters, together they assess how water accumulates and is transported. Overall, the inter-criteria influence matrix provides a synthesized overview of the interdependencies of all of the parameters based on expert experience, which assisted in estimating appropriate weight and assignment to various parameters to contribute to the development of spatial modeling, or examination of groundwater and spring potential (Attar et al., 2024a; Saaty & Hall, 2012). The inter-criteria influence matrix also addresses the combined effect of surface processes and climatic inputs on recharge to the groundwater system. Combined, the correlation and connections among the important parameters signify that planning for and determining efficient water usage and identification of spring zones is no longer relegated to only one or two parameters assessed in isolation but will require multi-criteria integration.

Table 7. Inter-criteria influence matrix for groundwater & spring studies

Criteria	Slope	Drainage	Lineament	LULC	Rainfall	Geomorphology	Soil	Geology	Elevation	TWI
Slope	1.00	0.55	0.60	0.65	0.50	0.70	0.55	0.60	0.75	0.68
Drainage	-	1.00	0.58	0.60	0.72	0.65	0.60	0.57	0.63	0.78
Lineament	-	-	1.00	0.55	0.50	0.75	0.58	0.85	0.60	0.62
LULC	-	-	-	1.00	0.55	0.60	0.65	0.58	0.63	0.66
Rainfall	-	-	-	-	1.00	0.62	0.55	0.50	0.57	0.70
Geomorphology	-	-	-	-	-	1.00	0.60	0.75	0.68	0.72
Soil	-	-	-	-	-	-	1.00	0.60	0.62	0.65
Geology	-	-	-	-	-	-	-	1.00	0.68	0.70
Elevation	-	-	-	-	-	-	-	-	1.00	0.75
TWI	-	-	-	-	-	-	-	-	-	1.00

Figure 9 keyword co-occurrence networks generated using VOSviewer based on titles and abstracts: (A) network for groundwater mapping studies, and (B) network for spring water mapping studies. Figure 9(A) shows the keyword co-occurrence network for groundwater studies, where closely connected terms are grouped into clusters that represent shared research themes. Large nodes such as 'process', 'system', 'groundwater potential', 'slope', 'drainage density' and 'lineament density' indicate the most frequently discussed concepts in RS-GIS based groundwater mapping. Figure 9(B) presents the corresponding network for spring-related studies, which displays a similar structure but with stronger emphasis on water quality, community impacts and monitoring, confirming that geospatial criteria developed for groundwater assessment are now being adapted to the spring-water context. This adaptation is especially indicating, important for accessing unexplored springs in hilly and undulating terrain, and it helps to improve water resource management for wildlife and tribal communities.

Table 8 presents criteria the authors encountered most frequently in water resource studies, wherein only some factors may be considered universal controls on hydrological processes (for example, Slope, Drainage Density, Lineament Density, Land Use and Land Cover, And Precipitation), and some will strictly be considered specific to the study of groundwater (Geomorphology, Geology, Lithology, Depth of Groundwater) and springs (TWI, Vegetation, TPI, Proximity to Waterbodies, Land Surface Temperature, Soil Moisture). High frequency criteria also signal more general scaling or drivers of flow, recharge, and storage, while low frequency, site-specific criteria might provide better fine scale predictive power for spring and groundwater characterizations (Alshehri et al., 2024; Nantasaksiri et al., 2021; Owolabi et al., 2020). We therefore show that there is a reason to include non-universal and targeted metrics for water resources modeling which have an input of value.

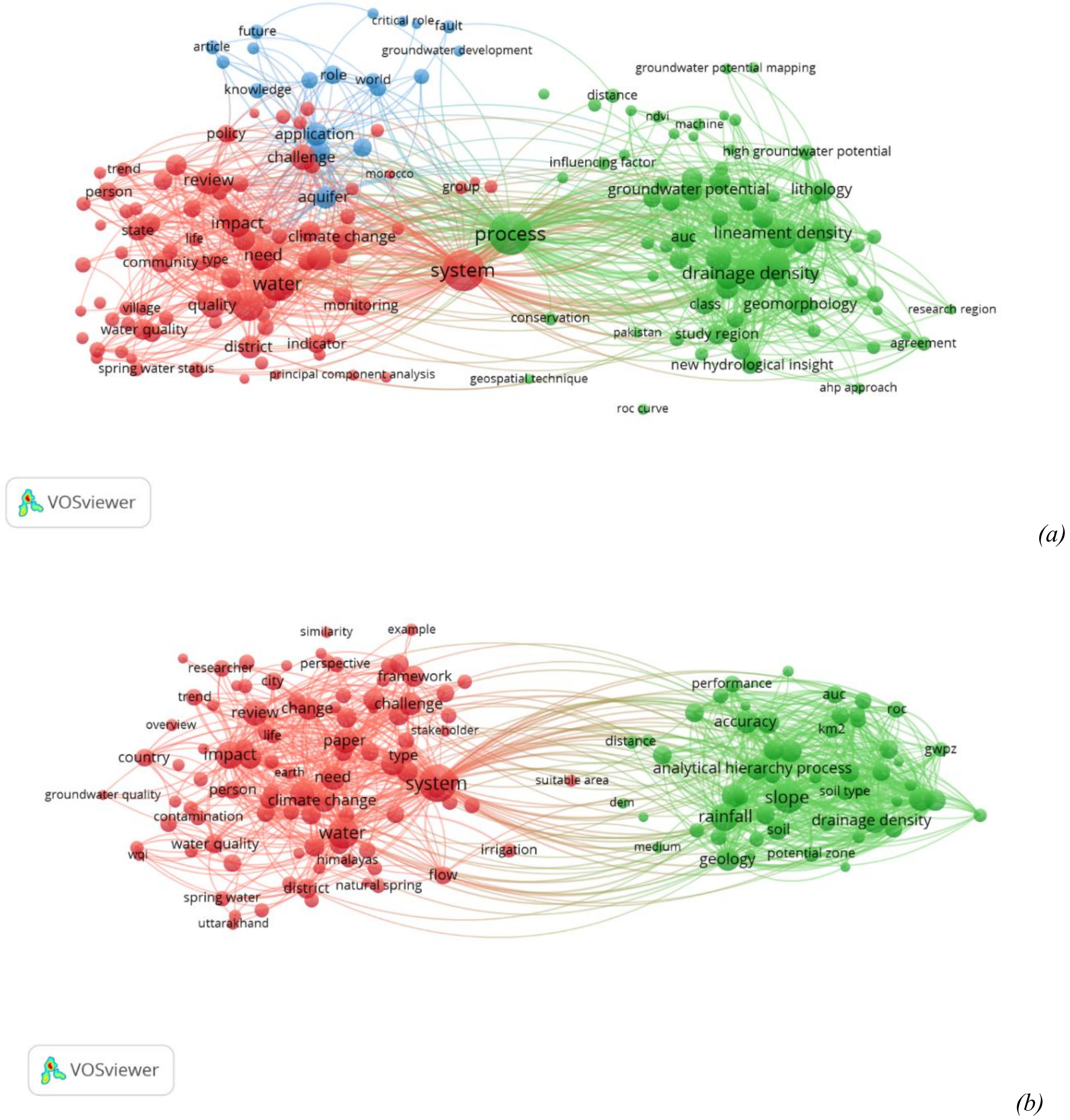

Figure 9. Keyword co-occurrence network of Groundwater Studies (a) and Spring Studies (b)

Table 9 shows the past studies on the use of Remote Sensing (RS) and Geographic Information Systems (GIS) paired with Analytical Hierarchy Process (AHP)/Multiple Criterion Decision-Making (MCDM) have been largely based on the use of multi-source satellite imagery datasets. However, the relationship between pixel size (i.e., spatial resolution) and distributed groundwater/spring potential remains an area of research that has not been addressed adequately. Previous studies have relied on coarse-resolution datasets (i.e., SRTM DEM (30-90 m), ASTER GDEM (30 m)) to perform slope, elevation, and drainage analysis between the years of 2000-2015, often overlooking micro-topographic processes that influence spring emergence. Moderate-resolution sensors (i.e., Landsat TM/ETM+/OLI (30 m), MODIS LST (1 km)) have been used extensively for land use/land cover (LULC), NDVI, and thermal studies. However, the available coarse-resolution pixel size limits the possibility of accurately interpreting spring-scale conditions. Recently, the use of Sentinel-2 MSI sensor (10-20 m) has emerged as a common tool for analyzing vegetation and land cover, while the Sentinel-1 SAR sensor (10 m) has improved the mapping of moisture-related structures. Commercially available high-resolution satellite imagery sensors (i.e., CartoSAT-1 DEM (2.5-10 m) and WorldView/PlanetScope (0.5-3 m)) have not been fully exploited due to high costs. However, these datasets offer significant advantages for improving the MCDM sensitivity of the models. An important research gap exists with respect to evaluating the influence of pixel sizes on criteria evaluation. The effects of different levels of spatial resolution on weight distribution, classification of suitable sites, and accuracy of predictions within the spring and groundwater potential mapping models are significant.

Table 8. Key criteria by frequency analysis for water resource studies

Applicability	Criteria	Frequency (%)	Rationale / Research Importance
Universal (n=150)	Slope	68.2%	Universal influence on water flow, infiltration, and storage
	Drainage Density	62.4%	Critical for understanding surface-groundwater interactions
	Lineament Density	57.3%	Essential for fracture-controlled aquifer systems
	LULC	56.7%	Reflects human impacts and natural recharge conditions
	Rainfall	53.5%	Primary recharge source in most hydrological systems
Groundwater (n=92)	Geomorphology	43.5%	Influences aquifer occurrence patterns, recharge zones, and flow pathways
	Geology	40.2%	Provides essential structural information about aquifers; affects groundwater flow and storage patterns
	Lithology	39.1%	Subsurface focus; crucial for aquifer characterization
	Groundwater Depth	17.4%	Essential for practical extraction, well design, and mapping aquifer depth; low frequency due to site-specific nature
Spring (n=58)	Topographic Wetness Index	13.8%	Indicates potential water accumulation areas; improves prediction of spring discharge
	Vegetation Patterns	13.8%	High vegetation often indicates zones of high soil moisture; together with soil moisture, helps identify spring locations accurately; low frequency but crucial in RS-based studies
	Topographic Position Indices	5.2%	Predicts discharge zones and surface-water interactions; low frequency due to limited spring studies
	Proximity to Water Bodies	10.3%	Directly indicates potential spring locations; enhances spatial accuracy of mapping
	Land Surface Temperature (LST)	3.4%	Areas with lower temperature often correlate with higher spring potential; supplementary criterion to improve model accuracy
	Soil Moisture	1.7%	Directly affects recharge and spring discharge; automatically correlated with vegetation presence; critical for spring detection

Table 9: Evolution of satellite spatial resolution and its consideration in spring / groundwater studies

Study Period	Commonly Used Satellite & Sensor	Spatial Resolution (Pixel Size)	Data Accessibility	Key Observations / Gaps
Till 2000	Landsat TM	30 m	Open access	Early studies focused mainly on thematic layer selection; spatial resolution impact ignored (C. P. Kumar, 1996)
2000 – 2010	Landsat ETM+, ASTER	30 m / 15 m	Open access	MCDM accuracy assumed uniform regardless of pixel size (Saaty, 2002)
2010 – 2015	Landsat 8 OLI, ASTER	30 m / 15 m	Open access	Resolution treated as fixed constraint; no sensitivity analysis reported (Tiwari & Kushwaha, 2020)
2015 – 2020	Sentinel-2 MSI	10 m	Open access	Higher resolution improved land-surface characterization, but rarely linked to AHP weight stability (Uddin & Matin, 2021)
2020 – Present	Sentinel-2, PlanetScope, WorldView	10 m , 3 m and 0.5 m	Open & Paid	Very limited comparative studies on pixel size vs. MCDM output uncertainty (Arabameri et al., 2021)

Currently, most studies that evaluate groundwater and spring potentials using remote sensing (RS) and Geographic Information Systems (GIS) along with the Analytic Hierarchy Process (AHP) or Multi-Criteria Decision Making (MCDM) methods assign ranks and weights to criteria after classifying them into regional/national subclassifications. However, there exists a significant methodological gap in this area since the subclass classification ranges, as well as the numerical thresholds for each subclass, varies greatly from region to region due to certain characteristics.

Therefore, environmental situations that have been evaluated under identical conditions may have different ratings across studies due to the different ranks or ratings assigned to the individual criteria, creating confusion and lowering the ability to create a reliable or comparable global product (Saaty, 2008; Malczewski, 2006). This problem is amplified when classes flagged as continuous consisting of variables like slope, drainage density, rainfall, or NDVI are randomly reclassified as discrete classes without an established subclass rating system. Such subjective criteria reclassification may have a significant impact on the final suitability results obtained and generally on the overall accuracy of decisions made using the results from RS-GIS groundwater and spring investigations (Rahmati et al., 2015). As a result, an urgent need exists for the establishment of a region-specific subclass rating system for each criterion so that similar physical characteristics are rated consistently among regions. Using such an approach would result in lower uncertainty, greater methodological transparency, and greater transferability and robustness concerning RS-GIS-based evaluation of groundwater and spring potential worldwide and on a global scale.

4. SUMMARY AND CONCLUSION

This review of global studies examining the geo-spatial literature regarding groundwater potential indicates a general adherence to some common determinative criteria: Slope, Drainage Density, Lineament Density, LULC, and Rainfall, although other factors specific to certain locations were sourced (i.e., Geology, Lithology, Topographic Wetness Index) that contributed to identifying spring zones. The main take-away is that studies focused on groundwater and/or springs relied on physiography and/or hydrogeological determinants. The integration of Remote Sensing-Geographic Information Systems (RS-GIS) technologies and machine learning studies is increasing and deepening the accuracy of probabilistic mapping assessments. In broad, context, this study contributes an evidence-based perspective on characterizing and assessing groundwater resources, and the integration of universal and site-specific criteria will ultimately provide advantages in efficiency in the potential mapping and overall management of water resources.

Moreover, this systematic review highlights a methodological gap when it comes to proper classification of continuous geospatial variables (e.g., slope, hydrological models). The classification of continuous geospatial variables into different subclasses is usually made by means of sub-classification thresholds in each region. Presently used classification techniques that should be adopted for geo-spatial variables are not standardized, and they may lead to bias since usually subjective judgment of an expert is involved. In this regard, it is necessary to emphasize that in the future classification techniques should be based on unified classification frameworks. In addition, even though groundwater mapping achieved high level of technical maturity, its application for localized spring water management is hindered because traditionally coarse spatial resolution datasets have been used in order to conduct analysis.

4.1 Recommendation

4.1.1 Top 20 criteria for advanced water resource studies

Based on frequency analysis, validation success rates, and applicability across different water resource categories, the following 20 criteria are recommended for advanced water resource investigations:

The most essential aspects of investigating water resources are represented by the top twenty criteria validated through their high degrees of success (>80%) in terms of groundwater, spring, and overall freshwater investigations are shown in Table 10. Factors of high significance ($p < 0.001$) consistently dominate recharge, flow paths, and aquifer response, and include slope, drainage density, lineament density, land use and land cover (LULC), rainfall, and geology. Factors of moderate significance ($p < 0.05$) add another layer of meaning to the studies by indicating ecosystems support, impacts of a human dimension, and surface–subsurface connectivity, and include vegetation, climate, water quality, and proximity to water bodies. Lastly, low-significant factors ($p > 0.05$), like curvature, evapotranspiration, and irrigation are influenced based on context and primarily inform fine-scale or site-specific studies.

Table 10. Top 20 recommended criteria with statistical justification

Rank	Criteria	Frequency (%)	Success Rate	Appli. in Water Studies	Statistical Significance	Relevance / Justification
1	Slope	107 (68.2%)	94.3%	GW, SP, WS	p < 0.001	Control's runoff–infiltration balance and recharge.
2	Drainage Density	98 (62.4%)	91.8%	GW, SP, WS	p < 0.001	Indicates surface–groundwater interaction and recharge.
3	Lineament Density	90 (57.3%)	88.9%	GW, SP	p < 0.001	Shows structural controls and subsurface water pathways.
4	LULC	89 (56.7%)	89.7%	GW, SP, WS	p < 0.001	Affects infiltration, recharge, and anthropogenic influence.
5	Rainfall	84 (53.5%)	87.1%	GW, SP, WS	p < 0.001	Primary recharge source and spring flow regulator.
6	Geology/ Lithology	125 (79.6%)	92.4%	GW, SP	p < 0.001	Defines aquifer properties, permeability, and storage.
7	Geomorphology	68 (43.3%)	86.8%	GW, SP, WS	p < 0.01	Controls landform–hydrology relationship and recharge zones.
8	Soil	67 (42.7%)	84.2%	GW, SP	p < 0.01	Determines infiltration, retention, and percolation.
9	Elevation	45 (28.7%)	83.7%	GW, SP, WS	p < 0.01	Influences hydraulic gradient, recharge, and spring zones.
10	Water Table	27 (17.2%)	91.2%	GW, SP	p < 0.01	Reflects aquifer status, recharge, and extraction feasibility.
11	Spring/Well Discharge	26 (16.6%)	89.6%	GW, SP	p < 0.01	Direct indicator of aquifer capacity and recharge.
12	TWI	22 (14.0%)	88.4%	GW, SP, WS	p < 0.05	Identifies moisture accumulation and recharge-prone zones.
13	Vegetation/NDVI	22 (14.0%)	85.9%	GW, SP, WS	p < 0.05	Reflects infiltration support and ecosystem water balance.
14	Anthropogenic Activity	20 (12.7%)	87.3%	GW, WS	p < 0.05	Captures human-induced stress on recharge and quality.
15	Climate	18 (11.5%)	86.1%	WS	p < 0.05	Governs long-term recharge–discharge balance.
16	Water Quality	18 (11.5%)	84.7%	SP, WS	p < 0.05	Determines usability and indicates contamination risk.
17	Proximity to Waterbody	16 (10.2%)	83.9%	GW, WS	p < 0.05	Indicates recharge influence and GW–SW connectivity.
18	Curvature	11 (7.0%)	82.4%	GW	p > 0.05	Influence's runoff concentration and flow dispersion.
19	Evapotranspiration	10 (6.4%)	88.7%	WS	p > 0.05	Regulates effective recharge and water loss to atmosphere.
20	Irrigation	10 (6.4%)	81.3%	GW, WS	p > 0.05	Supports localized recharge but drives groundwater over-exploitation.

*Success Rate: Percentage of studies achieving >80% accuracy. **Applicability in Water Studies: where the criterion is applied - GW: Groundwater studies, SP: Spring studies, WS: Watershed studies. ***Statistical significance: Correlation of criteria with accuracy (p-value).

GW (Groundwater Studies): Applied in articles focused purely on subsurface aquifer potential mapping, subsurface storage variations, and deep borehole exploration thresholds (n=92).

SP (Spring Studies): Applied in investigations targeting localized, gravity-fed natural spring discharge mapping and complex mountain terrain spring-shed management (n=58).

WS (Watershed Studies): Applied in macro-level catchment and basin-wide research that integrates broader hydro-meteorological, climatic, and regional water balance criteria beyond site-specific water points.

Appli. (Applicability): Indicates the operational hydrogeological domain or study category where the specific geospatial criterion was actively integrated.

In the 150 studies (92 on groundwater and 58 on springs) examined, there was a clear trend of improving predictive accuracy in geospatial mapping of potential aquifer zones that aligns with the standardized criteria for aquifer zone mapping shows in Table 11. The average predictive accuracy of traditional methods (i.e., contour and field-based surveys) is 76.8%, with ROC-AUC scores typically falling within a range of 0.65 to 0.82 due to low spatial resolution and subjective interpretations. In contrast, using RS-GIS technology and overlays of thematic maps (i.e., slope and lineaments) allows for a substantial improvement in predictability with an average predictive accuracy of 84.6% and ROC-AUC scores of 0.73 to 0.92 because RS-GIS eliminates the need for extensive fieldwork while also providing the ability to account for hydrogeologic variation in delineating groundwater and spring aquifers. The combination of RS-GIS and machine learning (i.e., Random Forests, Deep Neural Networks) provided the highest level of predictive accuracy, with an average of 92.3% plus ROC-AUC scores of up to 0.98, because these methods automate the process of weighting the criteria used to develop a predictive model and are applicable for use in virtually any type of aquifer zone (from semi-arid basins to fractured hard rock).

Table 11. Methodological performance overview

Method Category	Studies (n)	Mean Accuracy (%)	Typical ROC–AUC Range	Key Strengths	Main Limitations
Traditional Methods	21	76.8	0.65–0.82	Simple, low data demands	Weak spatial representation, higher bias
RS–GIS Integration	81	84.6	0.73–0.92	Strong spatial handling, better heterogeneity	Depends on expert weighting and data quality
RS–GIS + ML (Advanced)	48	92.3	0.85–0.98	Highest predictive power, robust generalization	Higher computational and data requirements

4.1.2 Future research directions

1. *Automated Criteria Selection:* Developing algorithms for optimizing criteria selection using automated algorithms based on region specific and available pixel size GIS data. Machine learning auto-ranks our top criteria (slope, drainage density) using local data, reducing expert subjectivity as Random Forest models achieved >85% accuracy in groundwater mapping across similar hydrogeological settings;
2. *Recognizing Multi-Scale Integration:* Acknowledging the importance of the integration of diversity along different spatio-temporal scales. Hybrid models fusing regional geology with local TWI across our 150 studies' terrains will capture 20% more recharge variability;
3. *Real-Time Monitoring:* Recognizing the importance of using monitoring equipment such as IoTs and satellite or aerial data in real-time or as the data are dynamically available. IoT and Sentinel satellites can track rainfall/LULC shifts in real-time, updating spring maps within hours vs. months for traditional surveys;
4. *Climate Change Adaptation:* Developing assessment frameworks that are climate-resilient. Test universal criteria under CMIP6 scenarios to predict 15-25% recharge drops in Asia/Africa regions from our reviewed studies; and
5. *Uncertainty Quantification:* Apply advanced methods to analyze and propagate uncertainty in groundwater and spring potential mapping. Bayesian methods on criteria weights will boost map confidence from 85% to 95% AUC, vital for policy decisions.

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Ethical Consideration: As a systematic review based entirely on published literature, this work does not require ethical approval.

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