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Bibliometric Mapping and Systematic Review of the Analytical Hierarchy Process (AHP) in Groundwater Potential Assessment Last Decade (2015-2024): Global Trend, Model Combination, Influence Factor, and Validation

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Abstract: The analytical hierarchy process (AHP) model has been deemed by researchers with various backgrounds as an alternative solution due to the rapid, flexible, cost-effective, and high accuracy of groundwater potential assessment based on expert judgment, especially in complex geological settings. This paper specifically reviews research trends, key influence factors, model techniques, and validation process in AHP for groundwater availability assessment using bibliometric mapping and systematic literature review (SLR). The result reveals that AHP has been consistently utilized over the past decade (2015-2024), commonly combined, and integrated with statistical and machine learning models to enhance accuracy. Thirty-eight influence factors were observed and categorized into 5 groups (geology, hydrogeology, geomorphology, hydrology, and socio-environmental). The five most influential factors with significant normalized weight values are lithology, geomorphology, drainage density, rainfall, and lineament density, respectively. Well yield and groundwater level are most validation data using receiver operating characteristic (ROC) and area under curve (AUC) approach to evaluate the model. Considering hydrogeological insight, multicollinearity, validation, and sensitivity analysis are crucial to reduce bias and enhance better understanding of site-specific factors.

Keywords : AHP; groundwater availability; bibliometric analysis; SLR

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Introduction

A global scarcity of groundwater has turned into a pressing issue due to excessive groundwater extraction (P. Saha et al., 2024). Around the globe, groundwater plays an essential role in the water demands of industries, households, and agriculture (Ozegin et al., 2023). To overcome that situation, mapping potential groundwater zones has emerged as a highly important target (Al-Djazouli et al., 2021; Saravanan et al., 2020), especially in regions with complex geological conditions (Wahyuni et al., 2024). Effective management and delineation of areas with significant water potential must rely on comprehensive and well-founded scientific studies (Al-Djazouli et al., 2021).

Several techniques have been applied to assess the potential occurrence of groundwater, both directly and indirectly by diverse researchers. Ground surveys were traditionally used for identifying groundwater potential zones such as well drilling (Gallardo, 2019) and geoelectrical surveys (Gallardo, 2019; Syamsuddin et al., 2019; Kang et al., 2020; Wahyuni et al., 2024). However, these methods require substantial labor and costs (Owolabi et al., 2020; Rehman et al., 2024). Many researcher or especially hydrogeologists, have extensively researched and employed diverse methods and approaches to develop the most appropriate groundwater potential (GWP) maps for their areas of interest (Thanh, Thunyawatcharakul, et al., 2022).

Recently, the analytical hierarchy process (AHP) employing thematic geo-environmental factors, and the incorporation of expert knowledge in identifying a groundwater potential (GWP), has garnered significant attention due to its ability to produce spatial models with high accuracy or good performance (Maheswaran et al., 2016; Singha et al., 2019; Echogdali et al., 2022; Thanh, Chotpantarat, et al., 2022, Ozegin et al., 2024), its efficiency, precision, and affordability (Yıldırım, 2021).

However, the primary challenge is the selection and weighting of the factors which can significantly impact the final groundwater potential map. It has been globally (Sulaiman et al., 2021; Thanh, Thunyawatcharakul, et al., 2022) reviewed, but its selection lacks explanations or justifications for why the researchers chose the parameters, as well as the rationale behind the weight assigned to each parameter used. It may depend on the researchers' disciplinary backgrounds, which may influence their perspectives such as researcher from geography background used geomorphology, weathered zone thickness, slope, lithology, soil, lineament, drainage and rainfall (Kumar & Krishna, 2018), from geology field (Owolabi et al., 2020) used surficial-lithology, lineament-density, drainage-density, rainfall-distribution, normalized-difference-vegetation-index, topographic-wetness-index, land use/land cover, and land-surface-temperature with consistency ratio of 0.09, from environmental science (Singh et al., 2024) used geology, geomorphology, LULC, drainage density, slope, rainfall, soil, TWI, and curvature with consistency ratio of 0.05.

From these situations, evaluating existing research on AHP in groundwater potential assessment becomes crucial to optimize decision-making processes and extract valuable insights for future research. The author aims to explore systematically and comprehensively the application of AHP in groundwater potential assessment, particularly focusing on global trend, model combination, influence factor, and validation through bibliometric mapping and systematic literature review technique. Because of conventional narrative review frequently lacking thoroughness (Tranfield et al., 2003)(Tranfield et al., 2003), both techniques have been deemed as an effective science mapping technique in handling a massive volume of data research by improving and providing a structured analysis, methodological thoroughness, reliable analyses, and integrated previous findings to efficiently optimize the existing knowledge for further research (Cobo et al., 2011; Briner & Denyer, 2012; Aria, 2017).

Methodology

This study employed a two-step approach with bibliometric mapping and a systematic literature review (SLR). Credible databases were retrieved from Scopus using specific queries in Title-Abs-Key, namely, “AHP AND Groundwater returned 1369 articles, of which 1105 were published last decade between 2015 and 2024. Refining the search to include “Potential” reduced the results to 442 articles. After excluding 14 papers that lacked indexed keywords, a total of 340 articles remained. Further filtering for geological terms such as “geology,” “lithology,” and “rock” resulted in a final dataset of 240 articles. From this dataset, 43 articles were retrieved and an additional 5 articles were included for detailed analysis which can only be accessed. Detailed inclusion and exclusion criteria are provided in Table 1.

Table 1. Summary of Inclusion and Exclusion Criteria

Criteria	Descriptions
	Inclusion
Language	Only articles written in English were included to maintain consistency and ensure that all studies could be evaluated without language barriers.
Publication Type	Articles must be either final versions of journal articles or conference papers to ensure that only peer-reviewed and formally published works are included.
Publication Year	Studies published between 2015 and 2024 were considered, as this period captures the most recent in last decade

Research Focus	The study must explicitly focus on groundwater potential assessment in analytical Hierarchy process (AHP) as a central methodology to evaluate and rank factors.
Geological Terms	The articles must include geological parameter or factor. The geological terms such as 'geology,' 'lithology,' or 'rock,' indicating the study's inclusion of geological factors in the analysis.
Keywords	Articles must contain specific keywords such as 'AHP,' 'Groundwater,' AND 'Potential' to ensure relevance to the topic and methodology being studied.
Exclusion	
Peer Review Status	Publications not subject to a peer-review process (e.g., preprints, reports, or unpublished theses) were excluded to ensure reliability and academic rigor.
Publication Type	Review articles summarizing existing studies without original research contributions were excluded to focus on primary data and results.
Methodology	Studies not applying AHP as part of their groundwater potential analysis were excluded, as the methodology is central to the research scope.
Context	Articles that did not include a geological context in their analysis were excluded, as these aspects are critical for assessing groundwater potential.
Language	Articles written in languages other than English were excluded to avoid translation inconsistencies and ensure accessibility of all included studies.
Publication Year	Studies published before 2015 or after 2024 were excluded to focus on recent developments and maintain temporal relevance to the research context.

Bibliometric Analysis using Biblioshiny

The rationale behind using bibliometric analysis first is to provide a global research landscape including research trends, most impactful articles, and influential studies in the field of AHP applications for groundwater potential assessment. After applying specific search queries such as "AHP AND Groundwater AND Potential," a total of 442 articles were retrieved. Tools used in Bibliometric mapping analysis is Biblioshiny in Rstudio (Aria, 2017) and the technique was adopted from https://bibliometrix.org/documents/bibliometrix Report.html

Systematic Literature Review using PRISMA

This stage is to systematically examine the literature identified as most relevant and impactful from the bibliometric analysis and then assess it using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow guidelines or Systematic Literature Review. This study investigates and assesses research trends and factors influencing groundwater potential in the analytical hierarchy process (AHP). It is considered for detailed and focused bibliometric analyses, as it ensures that only studies with a direct connection to geological aspects of groundwater potential are included. According to the PRISMA diagram, 48 articles were selected as the final dataset for detailed analysis. These articles were selected after applying the necessary filters and criteria during the screening process, ensuring their relevance to the objectives of the systematic literature review.

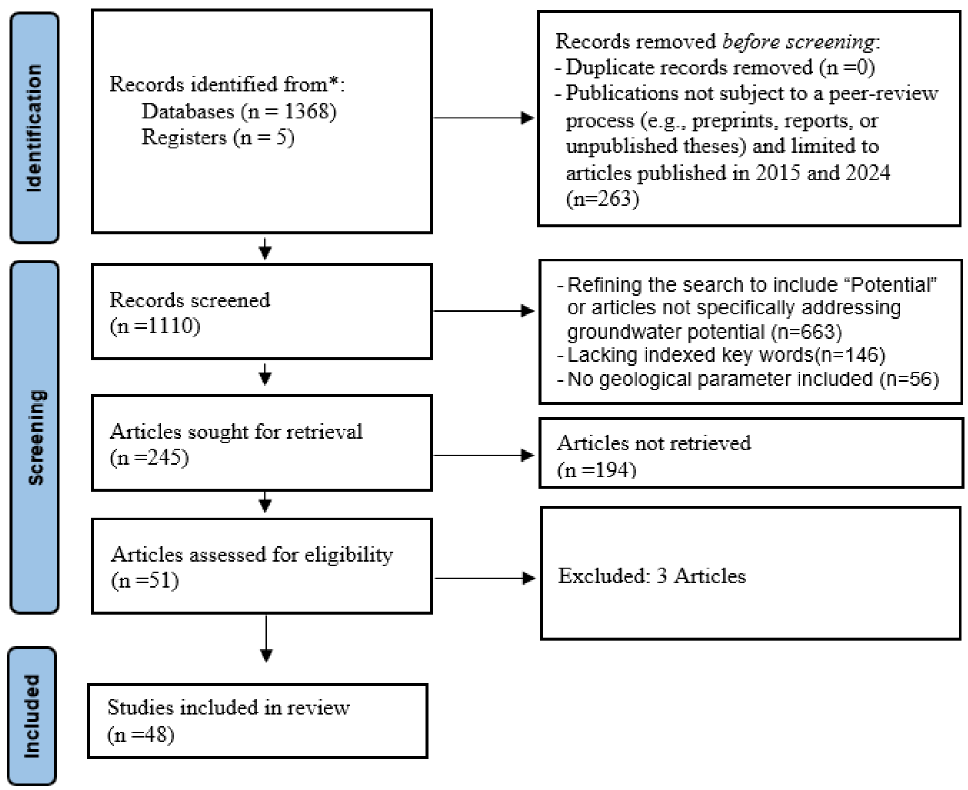


Figure 1. Diagram of Studies Identification Via Databases

To facilitate clarity and readability, Table 2 lists all abbreviations represent an influencing parameters and methods identified from the this studies.

Table 2. List of abbreviations

Abbreviation	Description	Abbreviation	Description
AHP	Analytical Hierarchy Process	ND	No Description
AS	Aspect	NDVI	Normalized Difference Vegetation Index
BWM	Best–Worst Method	RF	Recharge / Precipitation / Rainfall
C	Curvature	RG	Roughness
CR	Consistency Ratio	RO	Roughness *(alternative notation)*
DD	River Density / Drainage Density	RSP	Relative Slope Position
DtF	Distance to Faults	RS	Remote Sensing
DtL	Distance to Lineament	SD	Soil Depth
DtS	Distance to Stream	SGWS	Seasonal Groundwater Storage
DtW	Distance to Waterbodies	SL	Slope
DS	Dempster–Shafer	SO	Soil Texture
EL	Topography / Elevation	SPI	Stream Power Index
F-AHP	Fuzzy Analytical Hierarchy Process	SWAT	Soil and Water Assessment Tool
FD	Fault Density	TPI	Topographic Position Index
FR	Frequency Ratio	TRI	Topographic Ruggedness Index
FUCOM	Full Consistency Method	Tr	Transmissivity

GIS	Geographic Information System	TWI	Topographic Wetness Index
GL	Groundwater Level	WT	Weathered Zone Thickness
GM	Geomorphology	MIF	Multi-Influencing Factor
GWDA	Groundwater Depth (Post-Monsoon)	NA	Not Available
GWDB	Groundwater Depth (Pre-Monsoon)	HC	Hydraulic Conductivity
GWDF	Groundwater Depth Fluctuation	Hg	Hydrogeomorphology
IR	Irrigation	K	Karst
LD	Lineament Density	LST	Land Surface Temperature
LT	Geology / Lithology	LULC	Land Use / Land Cover

Results and Discussion

Advancements in Global Research Trends of AHP in Groundwater Potential Assessment

A total of 442 articles related to the application of the Analytical Hierarchy Process (AHP) in groundwater potential assessment were initially retrieved from the Scopus database during bibliometric analysis, reflecting the global research landscape on this topic. Approximately 13% of articles were excluded due to missing indexed metadata, such as keywords, during the screening stage. Detailed information on the inclusion and exclusion criteria, as well as the screening process and study selection, are provided in Table 1 and illustrated in the PRISMA flow diagram (Figure 1).

Highlighting the annual progress in AHP applications for groundwater studies over the last decade between 2015 and 2024, the trend shows a consistent rise in research articles from 2015 to a peak of 95 publications in 2023 reflecting growing interest in applying the analytical hierarchy process (AHP) for groundwater potential assessment. This growth is driven by advancements in decision-making tools and the growing recognition of AHP's effectiveness in identifying groundwater availability. A slight decline in 2024 likely reflects incomplete data for the ongoing year (Figure 2 and 3). India leads as the top contributor with approximately 180 articles and dominates with 430 broad collaboration research networks over the world. Ethiopia and Nigeria maintain strong positions with 80 and 61 researches, respectively, highlighting Africa's growing contributions to groundwater research (Figures 3 and 4).

The analysis of collaboration frequencies might highlight the strongest bilateral research connections in groundwater potential assessment. India and Saudi Arabia lead with the highest collaboration frequency (14), showcasing their strong partnership. Other notable connections include Saudi Arabia-China, and India-China, reflecting active engagement among major Asian countries. India also demonstrates robust collaborations with Ethiopia, Korea, and several other nations, including Egypt, Germany, Iraq, Malaysia, the United Kingdom, and the USA . Saudi Arabia shows significant links with Egypt, Morocco, and Portugal, highlighting its diversified partnerships. Additionally, regional collaborations such as Bangladesh-Malaysia emphasize intra-Asia cooperation. These patterns underline India's central role in global research networks, complemented by Saudi Arabia's active participation and the regional significance of smaller partnerships.

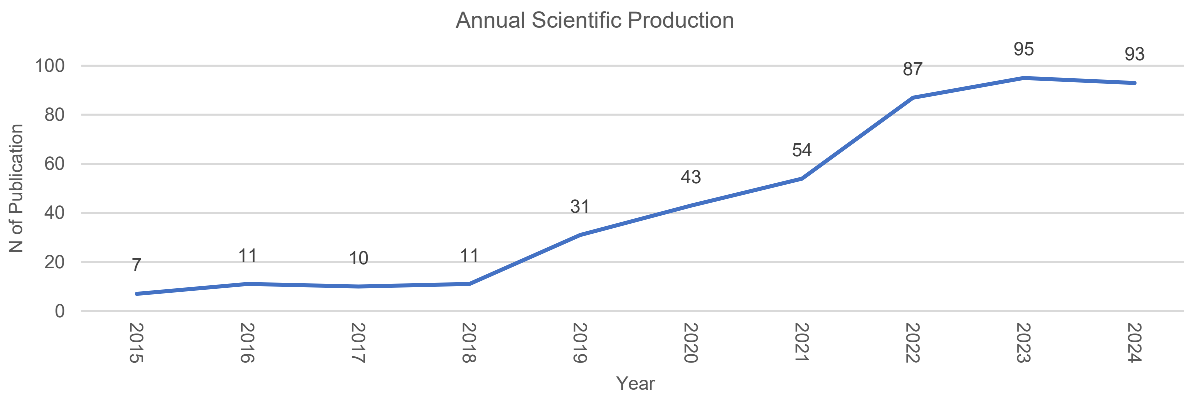


Figure 2. Annual scientific production of AHP Application in Groundwater Potential Assessment

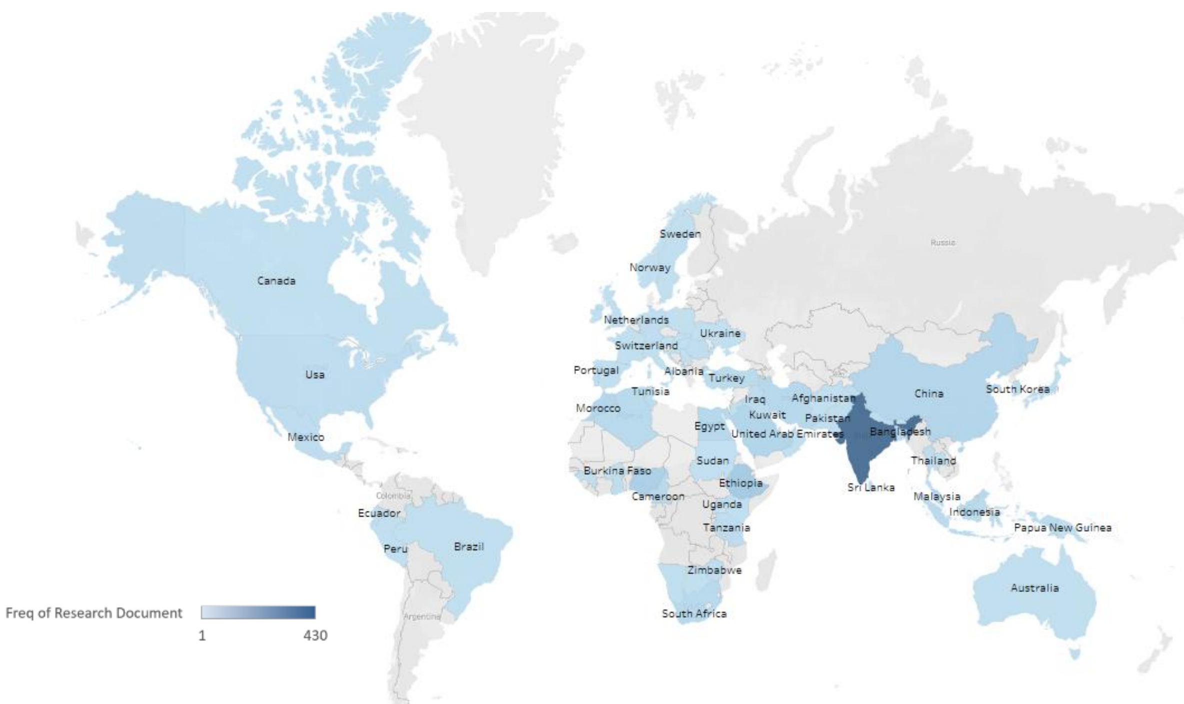
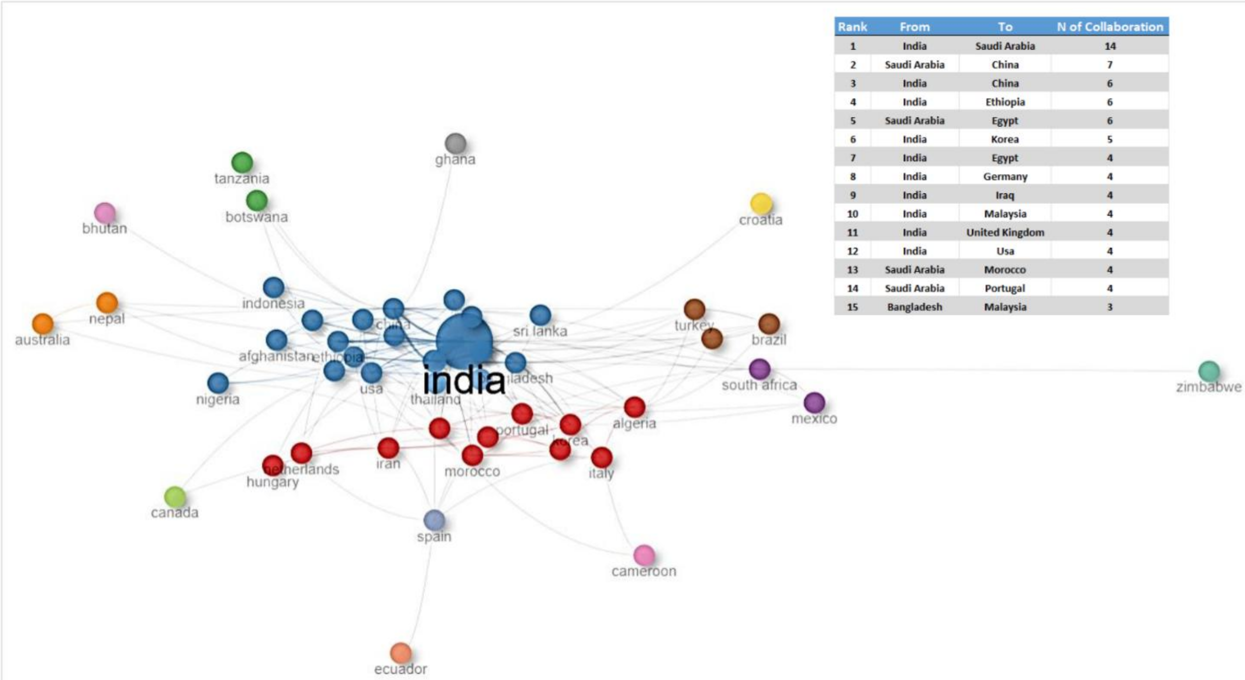


Figure 3. Geographical scientific production of AHP Application in groundwater potential assessment



Rank	From	To	N of Collaboration
1	India	Saudi Arabia	14
2	Saudi Arabia	China	7
3	India	China	6
4	India	Ethiopia	6
5	Saudi Arabia	Egypt	6
6	India	Korea	5
7	India	Egypt	4
8	India	Germany	4
9	India	Iraq	4
10	India	Malaysia	4
11	India	United Kingdom	4
12	India	Usa	4
13	Saudi Arabia	Morocco	4
14	Saudi Arabia	Portugal	4
15	Bangladesh	Malaysia	3

Figure 4. Global collaboration research related to AHP in groundwater availability assessment

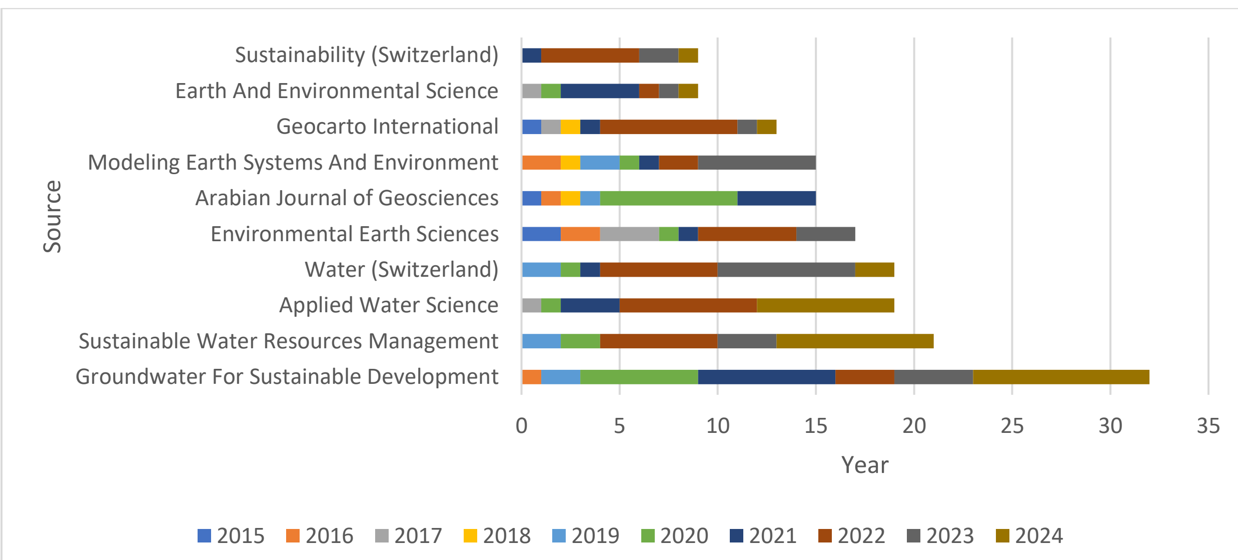


Figure 5. Top 10 journals publishing on groundwater potential using AHP in the Scopus database (2015 to 2024)

The ten top journals publishing research related to AHP on Groundwater Potential (GWP) selected by authors show varying trends over time (Figure 5). Groundwater for Sustainable Development leads in publications, especially in 2024, followed by Sustainable Water Resources Management and Applied Water Science. These journals reflect steady and growing engagement with AHP for GWP research, particularly in recent years. Those journals show a steady rise in AHP-related GWP research, suggesting it is an increasingly important global groundwater issue.

Table 3. Dataset of Systematic Literature Review

No	Method	Factor Control dan Weight	CR	Lithology	Validation Data	Accuracy	Reference
1	RS, GIS, AHP	LT(0.26), SL(0.058), LULC(0.17), EL(0.18), RF(0.20), DD(0.089), LD(0.05)	NA	Diluvial sand, fluvial sand, quicksand, river sediments, and sandy loess	Borehole, geophysical data, particularly gravity and wireline logging	No specific values	(Mohammed et al., 2024)
2	RS, GIS, F-AHP	GM(0.2207), LT (0.1544), LULC(0.1716), LD(0.1204), SO(0.115), DD(0.0731), RF(0.045), SL (0.0586), RG(0.0257), TPI(0.0151)	NA	Complex hard rock	Well yield and groundwater level	Precision of the groundwater potential: 82.97%	(Prapanchan et al., 2024)
3	RS, GIS-AHP, MIF	LT(0.35), LULC(0.23) SL(0.16), LD(0.12), DD(0.07), RF(0.04), SO(0.03)	NA	Sedimentary rocks and porous rock, while a low score was given to metamorphic rock due to low percolation rate	Well yield	AUC value: AHP (0.86), MIF(0.80)	(Meng et al., 2024)
4	RS, GIS, AHP	GM (0.215), LT (0.169), LD (0.133), SO (0.099), EL (0.088), SL (0.066), LULC (0.057), DD (0.045), RF (0.034), GWDB (0.026), GWDA (0.024), GWDF (0.019), TWI (0.014).	0.048	Sand, silt, clay with calcareous concretions, Feebly oxidized sand, silt and clay, Sandstone, clay, shale, conglomerate, brown and yellowish colour highly oxidized soil, quartz arenite, black slate, cherty phyllite, pyritiferous slate and phyllite, red and orange colour highly, chlorite sericite schist and quartzite and sandstone, shale with minor coal.	Groundwater Level	AUC: 0.818	(P. Saha et al., 2024)
5	RS, GIS, AHP	GM (0.242), LT (0.189), SL (0.128), LD (0.114), EL (0.080), LULC (0.069), SO (0.050), RF (0.045), DD (0.032), TRI (0.023), TWI (0.016), C (0.012).	0.01 - 0.074	Sedimentary, igneous, and metamorphic rock	Well yield	AUC: 0.784	(Guria et al., 2024)
6	RS, GIS, AHP	GM (0.35), LT (0.18), RF (0.12), LULC (0.09), LD (0.071), SO (0.06), NDVI (0.05), DD (0.04), SL (0.039)	NA	Coastal alluvial terrains	Yield, Groundwater Level, geophysical survey	The outcome of validation reveals that a strong correlation (80%)	(B. Saha et al., 2024)
7	RS, GIS, AHP	LT (0.42), SL (0.29), LD (0.15), GM (0.07), LULC (0.04), DD (0.03)	0.07	Porphyritic gneiss, porphyroblastic gneiss and granite gneiss, pegmatite, quartzite	Well yield	No specific values	(Sikakwe et al., 2024)

8	RS, GIS, AHP	GM(0.29), LT(0.15), LULC(0.13), SO(0.11), DD (0.09), SL(0.07), RF(0.05), TWI(0.05), C(0.05)	0.05	Sanugba group, ordovician-silurian baliana group, neoproterozoic siwalik sediments, fluvial sediments, sumna group, ordovician-devonian bad rinath granite, jaunsar group, neoproterozoic garhwal group, mesoproterozoic almora, proterozoic central crystalline, dan proterozoic	Groundwater Level	AUC: 89.9 %	(Singh et al., 2024)
9	RS, GIS, AHP, MIF	RF, GM, DD, LD, LT, SO, SL, EL, AS, LULC	NA	ND	Well yield, Groundwater Level	No specific numerical values mentioned	(Kathe et al., 2024)
10	RS, GIS, AHP	RF (0.196), TWI (0.114), GM (0.113), SL (0.108), LT (0.100), LD (0.099), SO (0.08), DD (0.063), NDVI (0.062), LULC (0.057)	0.095	Sedimentary, igneous, and metamorphic rock	Groundwater Level	Accuracy of 85% and a kappa coefficient of 0.77.	(Antony Ravindran et al., 2024)
11	RS, GIS, AHP	LT (0.174), LD (0.152), GM (0.152), RF (0.130), SO (0.130), DD (0.109), LULC (0.087), SL (0.065)	0.00 (Perfect score)	Sedimentary, igneous, and metamorphic rock	Well yield	Kappa index= 0.68 R^2 =0.64	(Twaha et al., 2024)
12	RS, GIS, AHP	LULC (0.13), SL (0.12), DD (0.13), LT (0.11), LD (0.10), TWI (0.16), RF (0.13), SO (0.13)	0.71	Archaean, cambrian, igneous rock, ordovician, and quaternary sediments and volcanic rocks	Groundwater Level	AUC: 0.736	(Opoku et al., 2024)
13	RS, GIS, AHP	RF (0.409), LULC (0.225), LT (0.163), LD (0.074), SL (0.051), DD (0.042), SO (0.036)	0.03	Silt, clay, admixture (alluvium), andesite–basalt, wetland, limestone, sand, water body, volcanic sediment, and conglomerate sandstone	NA	NA	(Beden et al., 2023)
14	RS, GIS, AHP	DD (0.64), LD (2.69), SO(0.87), LU(0.33), GM(1.16), LT (0.33)	0.085	Complex igneous-metamorfic rock and sedimentary formation made up of mainly sandstone and partly quartz-biotite-schist, and porphyritic Granit	NA	NA	(Ozegin et al., 2023)
15	RS, GIS, AHP	LT (0.33), LD (0.23), GM (0.16), SL (0.11), SO (0.07), RF (0.05), DD (0.03), LULC (0.02)	0.037	Limestone, alluvium, conglomerate, and limestone-sandstone.	Well yield	High coefficient of determination (No specific number mentioned)	(Maizi et al., 2023)
16	RS, GIS, AHP, MIF	LT (0.24), LULC (0.19), HG (0.16), EL (0.16), RF (0.11), DD (0.08), LD (0.05), SO (0.03)	0.021	Marl with thin limestone lenses, limestone and clays, sandstones and limestones , and alternating clayey sand, marl, sandstone, and fine limestone lenses, quaternary deposits	No specific, groundwater observation site	NA	(Farhat et al., 2023)

17	RS, GIS, AHP, SWAT	RF (0.1235), LT (0.1848), LULC (0.1263), SO (0.1422), DD (0.2109), C (0.0929), FD (0.1193)	0.097	Quaternary alluvium, carboniferous as good aquifer. In contrast, poor regions, primarily composed of silurian and jurassic strata, have low groundwater recharge capacity.	Well yield and spring	R^2 = 0.8 (well yield) and 0.74 (spring)	(Zhang et al., 2023)
18	RS, GIS, AHP, FR, RF	EL(0.2866), DtF(0.2866), DtW(0.1440), SL(0.1440), LT(0.0395), RF(0.0395), SO(0.0395), LULC(0.0203)	0.055	Carboniferous-permian, devonian, cambrian, cambrian ordovician, jurassic, cretaceous, ordovician, precambrian, permian, quaternary, silurian-devonian, silurian-devonian-carboniferous, tertiary, and triassic.	Well yield	AUC of 0.80, 0.76, 0.74, and 0.72 for the ensemble, RF, FR, and AHP models, respectively	(Thanh et al., 2022)
19	RS, GIS, AHP	SO (17.12), GM (16.63), LT(16.50), IR(13.97), LULC (13.43), DD(2.89), SL(10.40), LD (9.07), DD(2.89)	0.076	Alluvium and basalt	NA	NA	(Sahu et al., 2022)
20	RS, GIS, AHP, FR, AHP, FR-AHP	GM (0.2674), SL(0.2428), LT(0.1257), SO(0.1188), RF(0.0924), DD(0.0813), LD (0.0405), LULC(0.0310)	0.04	Sedimentary, igneous and metamorphic rocks	Geosite as indication of water accumulation : artificially excavated, constructed, or cavity	AUC: RF(72.47%), AHP 60.55%,	(Muavhi & Thamaga, 2023)
21	RS, GIS, AHP	GM (0.2352), DD (0.172), LD (0.1591), SL (0.1088), LT(0.0809), LULC (0.0776), RF (0.0622), EL(0.0395), SO (0.0385), GL (0.0263)	0.0059	Peninsular gneissic complex, charnockite, and rock types have lower infiltration capacity and lack weathering.	Groundwater Level	R^2 value for pre and postmonsoon was 0.90 and 0.83.	(Ravichandran et al., 2022)
22	RS, GIS, AHP	LT(0.33), SGWS(0.23), LD(0.16), GM(0.11), SO(0.08), SL(0.05), LULC(0.03), DD(0.02)	0.084	Sedimentary, igneous and metamorphic rocks	Well yield	Overall accuracy of 75%	(D. M. Das et al., 2022)
23	RS, GIS, AHP	LT(0.33), LD(0.23), GM(0.16), SL(0.11), SO(0.07), RF(0.05), DD(0.03), LULC(0.02)	0.002	Vanadiferous titano-magnetite, dolerite, hornblende-actinolite-chlorite schist, laterite, banded iron formation, chlorite schist	Well data (Not specific)	ROC-AUC showed accuracies of 79% and 82.1%.	(S. Das et al., 2022)
24	RS, GIS, AHP	LT(1.6), GM(1.4), SO(1.2), LULC(1.2), DD(1.0), SL(1.0), RF(0.8), LD(1.2), TWI(0.8), TPI(0.6), RO(0.6), C(0.6)	<0.1	Clay with caliche nodule and laterite, along with soft sediments like sand, silt, and clay, and granite gneiss. Smaller amounts of basalt, shale with ironstone and sandstone, quartzite, pegmatite, and additional sandstone and shale	Well yield	The GPZ map achieved 80.49% accuracy and a prediction score of 0.715 using AUC.	(Mukherjee & Singh, 2020)

25	RS, GIS, AHP	LD(0,4480), RF(0,2044), LT(0,1447), SL(0,0809), DD(0,0629), LU(0,0591)	0.033	Alluvium, limestone, sandstone, and granites	NA	NA	(Kessar et al., 2020)
26	RS, GIS, AHP	LT(0.49), K(0.28), GM(0.16), LD(0.07)	0.013	Granite, dolomite, limestone, basalt, shale, marl, and clay	Well yield	NA	(Hamdani & Baali, 2020)
27	RS, GIS, AHP	GM(0.254), LULC(0.183), DD(0.162), LD(0.133), SL(0.079), LT(0.025), SO(0.018), , RF(0.096), EL(0.096)	NA	Crystalline and sedimentary rock	Well yield, groundwater level	Descriptive Analysis	(Saranya & Saravanan, 2020)
28	RS, GIS, AHP	LT(0.39), GM(0.19), LD(0.13), DD(0.10), SO(0.08), SL(0.06), LULC(0.05)	NA	Deccan trap	NA	NA	(Rajesh et al., 2021)
29	RS, GIS, AHP	LT(0.220), GM(0.176), LULC(0.100), SL(0.100), LD(0.100), SO(0.100), FD(0.100), DD(0.052), RF(0.052)	0.003	Quaternary alluvium, terrestrial deposits, limestone, oligocene gravel and conglomerate, limestone, eocene argillaceous limestone, mesozoic dolomite, mesozoic calcshist, paleozoic crystalline rocks	Well yield, groundwater level	r=0.647	(Aykut, 2021)
30	RS, GIS, AHP, EBF	LT(0.281), DtL(0.159), GM(0.159), DtS(0.115), LULC(0.080), SL(0.056), DD(0.038), C(0.027), SO(0.024).	0.0362	Biotite-granite gneiss, sand, silt, and clay (unoxidized) laterite Ferruginous gritty sandstone and shale Sand, silt, and dark grey clay Sand, sandy loam, silt, and silt clay Lateritised boulder, conglomerate, and reworked laterite	Well yield	AUC value: EBF= 84.18%, EBF= 83.28%, AHP= 76.33%	(B. Ghosh, 2021)
31	RS, GIS, AHP, BWM, FUCOM	LU(0.218), LT(0.209), TRI(0.159), TWI(0.129), AS(0.082), DD(0.060), EL(0.053), C(0.038), RSP(0.032), SL(0.020)	NA	ND	Groundwater Level	NA	(Akbari et al., 2021)
32	RS, GIS, AHP	RF(0.24), SL(0.22), LT(0.21), LULC(0.21), TWI(0.06), DD(0.04), LST(0.02)	0.09	Quaternary sediment, S\sandstone, silty sandstone, silty/sandy mudstone, mudstone, shale, and dolerite	Well yield	R^2 = 0.901	(Owolabi et al., 2020)
33	RS, GIS, AHP	GM(0.28), RF(0.15), LD(0.14), LULC(0.13), SL(0.11), LT(0.08), DD(0.06), SO(0.05)	NA	Charnockite, laterite, metabasalt, metavolcanic, crossbedded quartzite, quartz chlorite schist with orthoquartzite,migmatites and granodiorite–tonalitic gneiss	Groundwater Level	Descriptive Analysis	(Saravanan et al., 2020)

34	RS, GIS, AHP	DD(0.416), SO(0.208), SL(0.0831), LT(0.139), GM(0.069), LULC(0.083)	0.074	Channel alluvium, older alluvium plain(c), older alluvium plain(s), terrace alluvium (depositional), and terrace alluvium (erosional)	NA	NA	(Banerjee et al., 2020)
35	RS, GIS, AHP	LT(0.22), LD(0.19), SL(0.16), LULC(0.14), DD(0.11), SO(0.11), RF(0.08)	NA	Clay with caliche concretion, calc-gneiss and granulite, pegmatite vein, granitic gneiss, hornblende schist, mica schist, and quartzite	Groundwater Level	Accuracy: 79.77%, Kappa co-efficient: 0.73	(D. Ghosh et al., 2020)
36	RS, GIS, AHP	LD(0.237), RF(0.170), LT(0.102), SL(0.066), DD(0.030), LULC(0.395)	0.1	Alluvial, sandstone, sands, basalts, and precambrian	NA	NA	(Al-Djazouli et al., 2021)
37	RS, GIS, AHP	LT(0.2571), LD(0.2286), GM(0.2000), SL(0.1143), LULC(0.0286), , SO(0.0857), DD(0.0857)	NA	Cordierite gneiss, dolerite, gabbro, granite, laterite, quartzite, sand, silt, clay admixture, syeno-granite, and warkalli beds	Well yield	No specific value	(Achu et al., 2020)
38	RS, GIS, F-AHP	LT(0.377), SL(0.271), SO(0.149), LULC(0.092), RF(0.065), DD(0.045), LD(0.001).	NA	Ophiolites, metamorphics, flysch, volcanics, limestone, and alluvium	Spring	No specific value	(Şener et al., 2018)
39	RS, GIS, AHP	LT(0.178), LD(0.178), LULC(0.133), SD(0.100), GL(0.078), DtS(0.061), DD(0.049), RF(0.039), EL(0.032), C(0.025), SPI(0.019), SL(0.015), TWI(A0.011), AS(0.010)	0.03	Complex igneous-metamorpic rock and sedimentary rock such as sand and silt, pondicherry, sands (coastal/alluvial), altered sequence of sand, shaly sandstone, limestone, marl, conglomerate, and clay with limestone.	Well yield	AUC = 76.90 %	(Jothibasu & Anbazhagan, 2016)
40	RS, GIS, AHP	LT(0.33), LD(0.23), GM(0.16), L(0.11), SO(0.07), RF(0.05), DD(0.03), LULC(0.02).	0.01	Sandstone, laterite, boulder beds, schist, basalt, granite, and gneiss	Well yield	R^2=0.76	(Murmu et al., 2019)
41	RS, GIS, AHP	GM(0.33), WT(0.23), SL(0.16), LT(0.11), SO(0.07), LD(0.05), DD(0.03), RF(0.02).	NA	Alluvium, sandstone, shale, coal, granitoid gneiss, phyllite and mica, schist, quartzite, and mine	Well yield	AHP had good prediction accuracy (AUC = 75.45%).	(Kumar & Krishna, 2018)
42	RS, GIS,AHP, FR, RF	LT(0.317), GM(0.215), SL(0.155), DD(0.117), LULC(0.079), LD(0.053), RF(0.037), SD(0.027).	0.04	Marine sediment, alluvium, and basalt	Well yield, Groundwater Level	FR: 75%, IF (71%) and AHP (70%)	(S. Das, 2019)
43	RS, GIS, AHP	SL(0.0275), LT(0.0697), DD(0.137), LULC(0.260), GM(0.5051)	NA	Clay, granite/quartzite, laterite, QF gneiss, and Hbl.biotite gneiss	NA	NA	(Siva et al., 2017)

44	RS, GIS, AHP	RF(2.49), LD(1.84), GM(1.53), SL(1.29), DD(1.05), SO(0.86), LULC(0.69), DtW(0.61), LT(0.39), EL(0.25), LST(0.20)	0.09	Alluvium, clay, clayey sands, and shale, clays and shale with limestone, clays, sandstone, lignite, and shale, coal, sandstone, and shale, false-bedded sandstones, coal, and shale, older granite, sands and clays, sands, clays, and mangrove swamps, shale and mudstones, undifferentiated basement complex with pebble beds, undifferentiated meta-sediments.	Well yield	Accuracy=81.25%	(Ozegin & Ilugbo, 2024)
45	RS, GIS, AHP	RF(3.2), Tr(1.57), HC(1.33), GM(1.15), SL(0.99), DD(0.85), SO(0.73), LULC(0.63), DtW(0.53), LT(0.43), C(0.35), EL(0.28)	0.0136	Alluvium, the bende ameki group, coastal plain sands, the imo clay-shale group, and the lignite formation	Well yield	Accuracy=88.89%	(Ozegin et al., 2024)
46	RS, GIS, AHP, MIF	LT(0.38), GM(0.24), LULC(0.16), DD(0.10), SL(0.06), RF(0.04), SO(0.03)	-0.009	Alluvium (sand/silt dominant), sandstone, shale, coal, laterite, dolerite/amphibolite (basic rocks), quartzite, metamorphic rocks, and granite	Well yield	R^2= 0.59	(M. Kumar et al., 2022)
47	RS, GIS, AHP, DS	LD(0.24), GM(0.16), SL(0.16), LT(0.12), SO(0.12), DD(0.12), LULC(0.08)	NA	Alluvium, amphibolite, augen gneiss, chlorite schist, coarse grained porphyritic granite, dolerite, fine grained leucogranite, granite, granite gneiss, grey sand silt and clay, medium grained leucogranite, medium grained pink granite, meta basalt, metabasites, metasediments, migmatite, oxidized sandy silt–clay and quartzo feldspathic sand, oxidized silt–clay with calcareous nodules and micaceous sand, pegmatite/ quartzofeldspathic veins, porphyritic coarse grained granite, porphyritic granite, pyroxenite, quartz-biotite schist, quartz sericite schist, quartzite, silt–clay with calcareous nodules and quartzo-feldspathic sand.	Well yield	AUC for AHP =76% DS= 79%	(Pandey et al., 2022)
48	RS, GIS, AHP	GM(0.40), LD(0.20), LT(0.18), SL(0.13), LULC(0.038), DD(0.026), TWI(0.015), TRI(0.011)	NA	Limestone, sandstone, and shale	Groundwater Level	ROC of training and testing accuracies of 0.82 and 0.810.	(Moharir et al., 2023)

The explanation of abbreviations is provided in Table 2

AHP-Based Model Combinations in Groundwater Potential Assessment

The analytical hierarchy process (AHP) method was originally developed by Thomas L. Saaty in the 1980s, which is a measurement theory that uses pairwise comparisons and depends on expert judgments to establish priority scales for each variable (Saaty, 2008) to solve a complex decision problem (Thungngern et al., 2015; Diriba et al., 2024). The earlier use of the Analytic Hierarchy Process (AHP) in relation to water and groundwater assessment was traced back to the early 1990s and 2000s, such as water resources policy and management (Hobbs et al., 1992; Mei et al., 1989), and groundwater potential (Srivastava & Bhattacharya, 2006; Ould et al., 2007). The AHP method has been widely used in recent decades and has proven successful in mapping groundwater potential zones in arid, semi-arid, and also areas with hard rock characteristics (Elvis et al., 2022; Nainggolan et al., 2024) which can be essential for planners and decisionmakers in regions with comparable climatic and geological settings (Meng et al., 2024). The systematic analysis of AHP techniques on weighted parameters, in a cost-effective manner, is a detailed map of groundwater potential areas using the GIS by integrating all thematic maps (Hamdani & Baali, 2020).

Recently, the application technique of the Analytical Hierarchy Process (AHP) is predominantly assisted by remote sensing and GIS in groundwater potential assessment, although they may vary slightly depending on the field background of the researchers, which can influence their perspectives such as geology (Farhat et al., 2023; Maizi et al., 2023; Meng et al., 2024; Prapanchan et al., 2024; B. Saha et al., 2024), environmental (Mohammed et al., 2024; Singh et al., 2024), hydrology and water resources (Opoku et al., 2024; Twaha et al., 2024), geography (D. Ghosh et al., 2020; B. Ghosh, 2021; Guria et al., 2024; P. Saha et al., 2024), agriculture (D. M. Das et al., 2022; Ravichandran et al., 2022), civil engineering (Saranya & Saravanan, 2020; Saravanan et al., 2020), remote sensing (Kumar & Krishna, 2018; Şener et al., 2018), etc. The standard procedure of Saaty's original AHP compared to its adaptation for groundwater assessment is provided in Table 4 as below.

Table 4. Comparison Between Saaty's Original AHP and Its Adaptation in Groundwater Assessment

Original AHP by Saaty (2008)	**AHP in Groundwater Potential Assessment**
Define the problem and determine the kind of knowledge sought.	Define the groundwater potential zones and identify the influencing or conditioning factors based on site specific.
Structure the decision hierarchy from the top (goal) to intermediate levels (criteria) and the lowest level (alternatives).	Build a hierarchy framework with the goal (groundwater potential assessment), followed by criteria (influence factors), and finally alternatives (specific zones) where the dataset is commonly extracted and compiled using geographic information system tools such as ArcGIS and QGIS. After determining the criteria, some researchers (Mukherjee & Singh, 2020; S. Das et al., 2022; B. Ghosh, 2021; Guria et al., 2024; Opoku et al., 2024; Antony Ravindran et al., 2024; P. Saha et al., 2024; Ozegin et al., 2024) also conduct multicollinearity analysis to evaluate and avoid strong linearity in each criteria or parameters of conditioning factors for final criteria.
Construct a set of pairwise comparison matrices. Each element in an upper level is compared with elements in the level immediately below it.	Develop a matrix for pairwise comparisons for final criteria comprising conditioning factors.
Use the priorities from comparisons to weigh priorities in the level immediately below and obtain global priorities.	Assign weights to all criteria or conditioning factors based on their relative importance, then determine priority for each zone verified using the consistency ratio (CR) of the matrix based on the consistency index (CI) and the random

	consistency index (RCI) where CR should be less than or equal to 0.1. Site specific consideration is crucial to determine relative importance such as geological settings as conducted by (Mukherjee & Singh, 2020). However, most studies do not consider it.
Continue the weighing and adding process until final priorities are determined.	Evaluate and repeat the process until CR is less than or equal to 0.1. Thus, perform weighted overlay analysis and visualize groundwater potential map.
	The final step involves validation using well data to assess the accuracy of the groundwater potential distribution map and sensitivity analysis to understand the influential factors (Mukherjee & Singh, 2020); D. Ghosh et al., 2020; Kumar & Krishna, 2018; S. Das et al., 2022; M. Kumar et al., 2022; M. Kumar et al., 2022; Pandey et al., 2022; Pandey et al., 2022, Meng et al., 2024). However, some researchers do not validate the models due to a lack of field data.

A review of literature analysis reveals that researchers have been using the analytic hierarchy process with some combination approaches to enhance accuracy and compare models in delineating the groundwater potential zones. All researchers employed AHP with Geographic Information Systems (GIS)-based approaches using remote sensing techniques as a tool to extract, compute, analyze, and visualize the data. These tools are essential and efficient for assessing spatial groundwater potential reliably (Shekhar & Pandey, 2015; Kathe et al., 2024; P. Saha et al., 2024). The data reflects the key topics and concepts associated with groundwater potential assessment using analytical hierarchy process (AHP) research, categorized by co-word network analysis (Table 5 and Figure 7), showing that groundwater potential and remote sensing with betweenness values of 61.5615 and 45.382, respectively, indicate their relatively high relationship.

AHP has been combined with many techniques such as multi influencing factor (MIF) comparing to AHP (Meng et al., 2024) and integrated with RS, GIS, AHP, and MIF techniques to enhances the comprehensive understanding of groundwater potential. MIF technique also can integrate and synthesize the influencing factors by compositing weights of AHP method to MIF values (Kathe et al., 2024) and to determine proper factor weighting and reduce uncertainty (Farhat et al., 2023).

Fuzy-AHP (Prapanchan et al., 2024) uses fuzzy logic implementing triangular fuzzy scale which is more complicated than basic AHP, but the concept is similar which relies heavily on expert judgments. However, it offers a suitable method for assessing result consistency, thus reducing bias within the decision-making process. Recently, AHP can be powerful by integrating with machine learning to identify influencing variables and hidden relationships between the inputs and outputs in groundwater potential assessment (Díaz-Alcaide & Martínez-Santos, 2019) to address the limitation of the AHP on expert's judgement dependence.

Frequency ratio (FR) and random forest (RF), a statistical algorithm in machine learning can measure relationships between factual quality groundwater and influencing factors. It also calculates the importance of influencing factors based on ground truth data (Thanh, Chotpantarat, et al., 2022), and hybrid model AHP and ML was performed by (Thanh, Chotpantarat, et al., 2022; Muavhi & Thamaga, 2023) to understand more detail of groundwater potential characterization. To delineate groundwater potential zone, (Zhang et al., 2023) used Soil and Water Assessment Tool (SWAT) combined with AHP to estimate rain fall and groundwater recharge variable as part of influence factors which improved the GWP accuracy

(Muavhi & Thamaga, 2023). AHP was also combined with Best-Worst Method (BWM), Full Consistency Method (FUCOM) by (Akbari et al., 2021) to classify groundwater potential maps.

Table 5. Bibliometric Co-Word Network Analysis

Node	Betweenness	Closeness	PageRank
AHP	912.7439	0.0208	0.2931
groundwater potential	61.5615	0.0141	0.0930
remote sensing	45.3819	0.0145	0.1073
sensitivity analysis	0.5118	0.0112	0.0145
remote sensing and gis	0.4959	0.0112	0.0153
frequency ratio	0.3312	0.0111	0.0143
random forest	0.1712	0.0109	0.0086
weighted overlay analysis	0.1127	0.0112	0.0158
MIF	0.1115	0.0112	0.0146
ROC	0.0788	0.0114	0.0141
machine learning	0.0330	0.0109	0.0069
weighted overlay	0.0055	0.0110	0.0146
fuzzy-ahp	0.0034	0.0108	0.0087

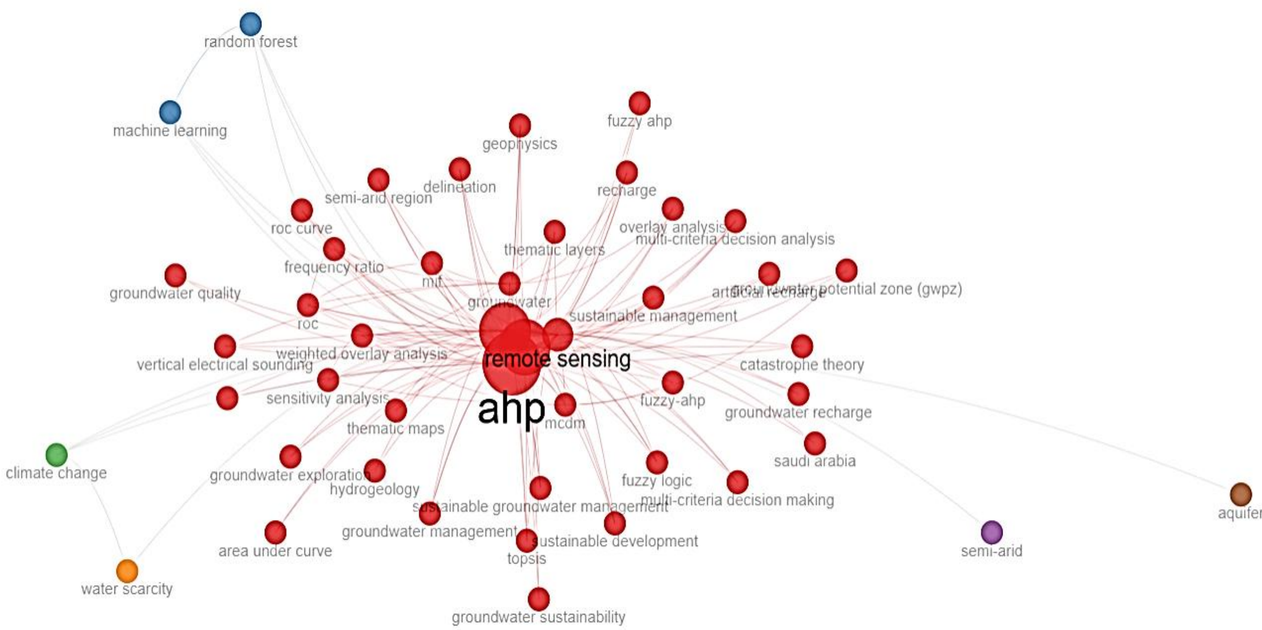


Figure 5. Bibliometric Co-Word Network Analysis

Key Factors Influencing Groundwater Availability

In AHP, Groundwater potential (GWP) studies are predominantly developed based on a range of factors, The AHP was applied to determine whether or not additional parameters should be included in the model and to capture the expert judgements of hydrogeologists on the relative importance of parameters (Josephs-Afoko et al., 2018). The ranks and weights are assigned to each parameter and the different classes based on their relative contribution for the potentiality (S. Das, 2019).

Derived from a comprehensive systematic review of 48 articles, a total of 38 influence factors as key parameters commonly used in groundwater potential studies was identified (Figure 6). The author classifies them into five categories namely geology, hydrogeology, hydrology, geomorphology, and the socio-environment category (Table 6). Among all influencing factors, lithology and geomorphology had the greatest impact on groundwater potential, as indicated by their highest frequency and assigned weights, respectively. Their equal frequency suggests that they have similar levels of impact on groundwater potential, playing a crucial role in the analysis.

Table 6. Categories of Parameters Affecting Groundwater Potential

Category	Influence Factors
Geology	Lithology (LT), Soil Texture (SO), Soil Depth (SD), Kars (K), Fault Density (FD), Distance to Faults (DtF), Weathered Zone Thickness (WT)
Hydrogeology	Groundwater Depth Pre-Monsoon (GWDB), Groundwater Depth Post-Monsoon (GWDA), Groundwater Depth Fluctuation (GWDF), Seasonal Groundwater Storage (SGWS), Groundwater Level (GL), Hydrogeomorphology (Hg), Transmissivity (Tr), Hydraulic Conductivity (HC).
Hydrology	Recharge/Precipitation/Rainfall (RF), Lineament Density (LD), River Density/Drainage Density (DD), Stream Power Index (SPI), Distance to Waterbodies (DtW), Distance to Stream (DtS), Distance to Lineament (DtL), Land Surface Temperature (LST), Irrigation (IR)
Geomorphology	Geomorphology (GM), Topography/Elevation (EL), Slope (SL), Roughness (RG), Curvature (C), Topographic Position Index (TPI), Topographic Wetness Index (TWI), Topographic Ruggedness Index (TRI), Relative Slope Position (RSP), Aspect (AS).
Socio-environment	Land Use/Land Cover (LULC), Normalized Difference Vegetation Index (NDVI)

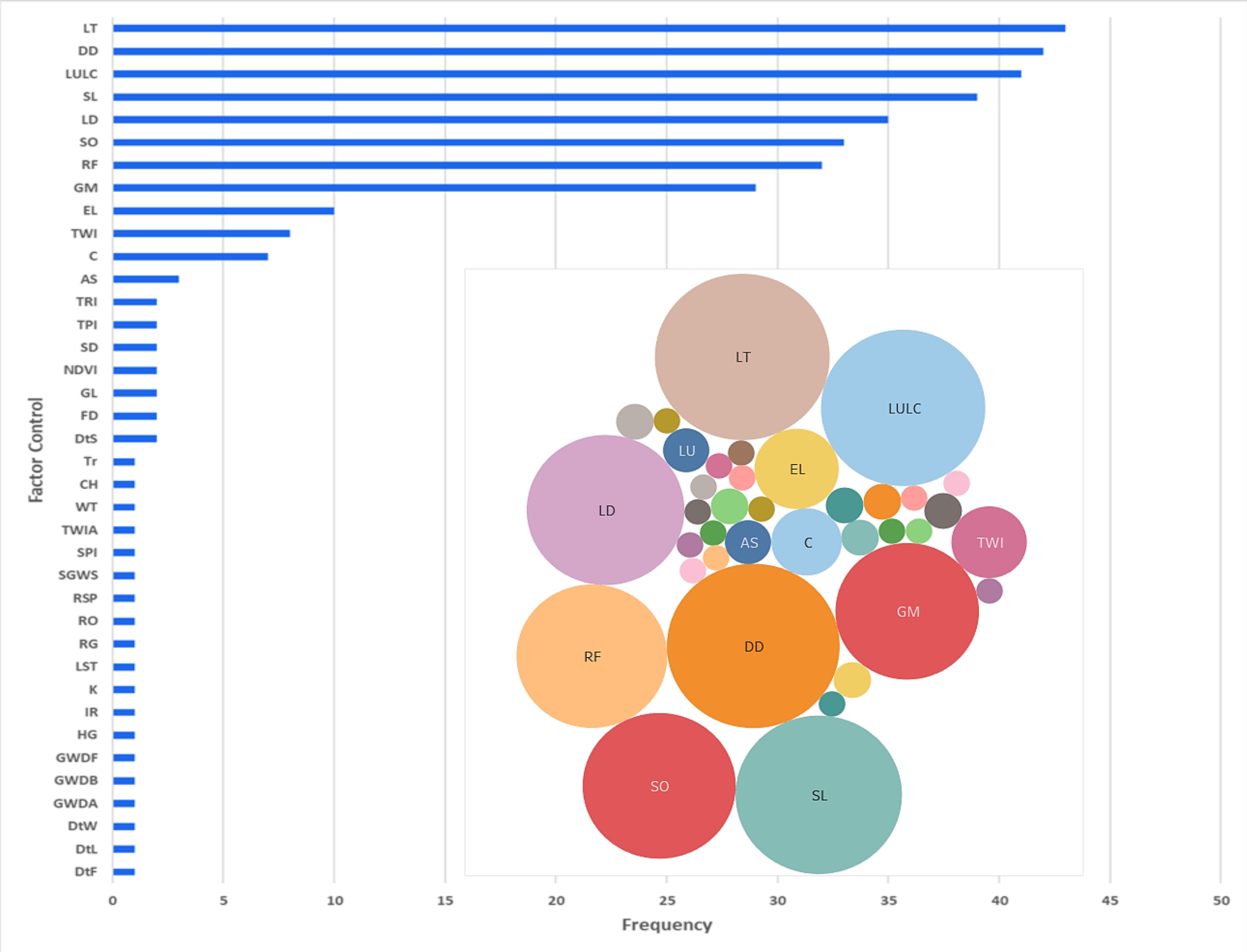


Figure 7. Frequency of influence factors analyzed in GWP studies from 2015 to 2024.

The author determines **Figure 7** by compiling each parameter is assigned first rank (the highest weight), indicating that the researcher considers this factor to be the most influential in determining groundwater potential in their study. Following the ranking process, a weight normalization procedure is applied to ensure that all parameters contribute proportionally to the final outcome. Normalization aims to adjust the weights of each parameter to allow for fair comparison, thereby providing an objective assessment of each factor's influence on the delineation of groundwater potential zones.

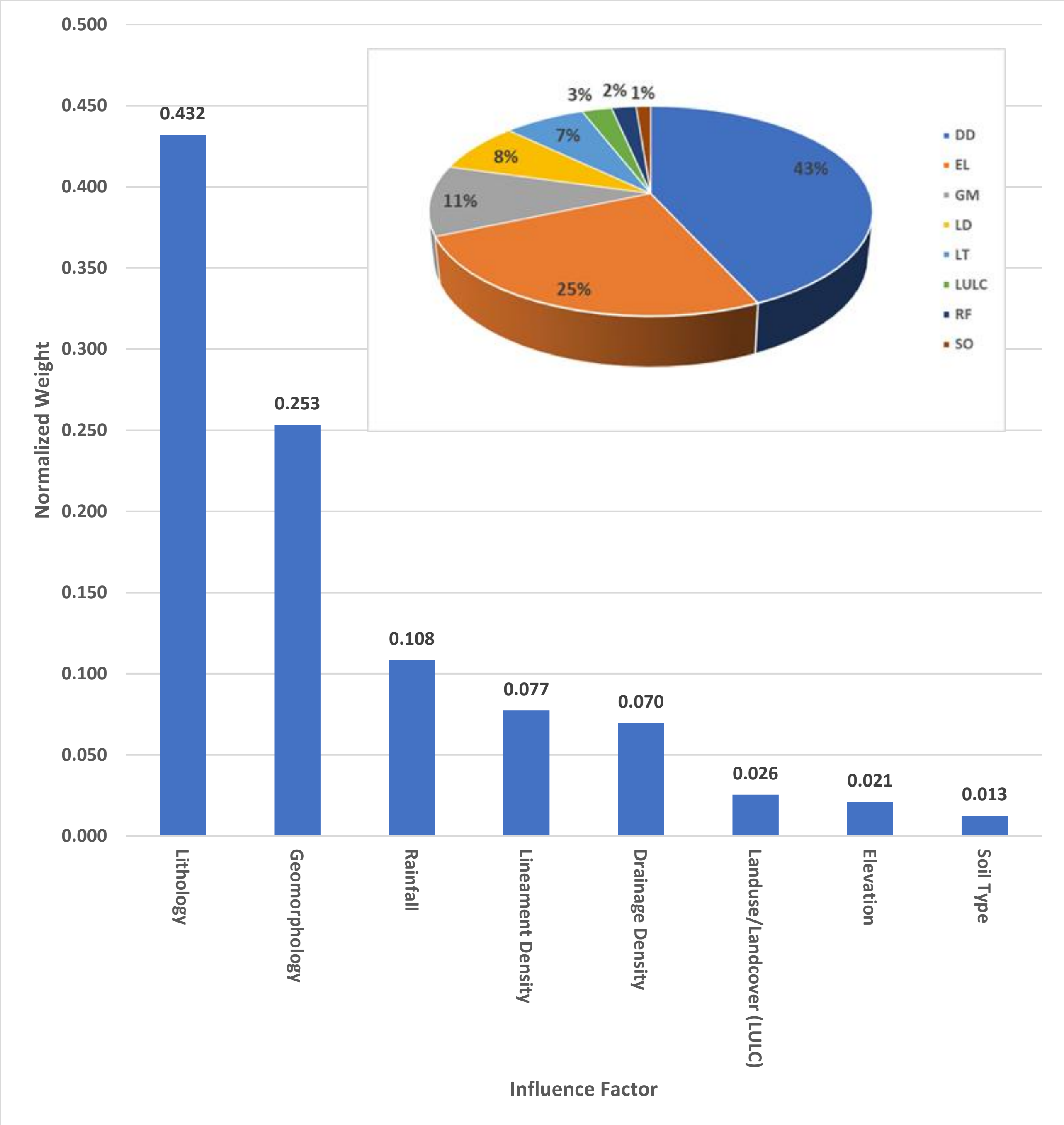


Figure 8. Highest weighted influence factors

Figure 8 shows that there are eight parameters with highest weight namely lithology (LT), geomorphology (GM), drainage density (DD), rainfall (RF), lineament density (LD), land use/land cover (LULC), elevation (EL), and soil type, (SO). Only five parameters with significant normalized weight value (≥ 7%) namely lithology (LT), geomorphology (GM), rainfall (RF), lineament density (LD), and drainage density (DD) are described below.

Geology Parameter (LT)

The term "geology parameter" is used to refer to both geology and lithology, as some researchers may use either term, or both interchangeably. It refers to type of rock. Lithology with half of total percentage weight or 43.2%, is crucial to be considered as the most influential parameter to groundwater availability as the hydrological significance of each geological setting and assigned weights according to the aquifer characteristics (Mukherjee & Singh, 2020). The information of specific lithology is presented in Table 2. Groundwater fills the voids, joints, and pores within geological strata and formations (Achu et al., 2020; Owolabi et al., 2020).The lithology type significantly influences groundwater supply, occurrence, movement and storage where the aquifer's ability to retain water (Achu et al., 2020; Rajesh et al., 2021; Meng et al., 2024; P. Saha et al., 2024). Sedimentary and porous rocks (Guria et al., 2024; Meng et al., 2024; Singh et al., 2024) given high weight such marine sediment (S. Das, 2019), fluvial sediment (Mohammed et al., 2024), alluvial (B. Saha et al., 2024), limestone and dolomite a low score due to their low percolation rate (Meng et al., 2024), coarse clastic sediments, and laterite (Twaha et al., 2024). When the rocks are generally poor aquifers except when weathered and fractured (Sikakwe et al., 2024), metamorphic rocks were assigned due to their cracks, which allow water to infiltrate easily (Hamdani & Baali, 2020).

Geomorphology (GM)

Geomorphology, which describes the landforms of a region (Prapanchan et al., 2024; P. Saha et al., 2024) with weight of 25.3.2%, is a key factor in controlling the subsurface movement of groundwater (Kumar & Krishna, 2018). Among these geomorphic landforms, alluvial tracts, lake bodies, and flood plains have a high chance of groundwater potentiality due to their higher probability for groundwater recharges and water retention capacity (P. Saha et al., 2024). However, researcher who interpreted GM as most impact to groundwater availability, integrates to soil, lithology, and slope characteristic such Pediplain (Saravanan et al., 2020; Prapanchan et al., 2024), older alluvial plain due to high permeability and infiltration (Guria et al., 2024; B. Saha et al., 2024), weathering dissected denudational hills tend to be very poor infiltration rates (Guria et al., 2024), flood plain (Saranya & Saravanan, 2020; Ravichandran et al., 2022), a hilly Indian state, faces with groundwater recharge due to steep slopes and high runoff, with snowy, high-altitude northern regions and southern flood plains favorable for water retention and recharge (Singh et al., 2024), valleys and flat plains (Muavhi & Thamaga, 2023), and river/Waterbody (Kumar & Krishna, 2018).

Rainfall (RF)

Rainfall is deemed a primary source for groundwater recharge and most influential factors for groundwater availability with weight of 10.8%. The intensity and duration of precipitation significantly influence infiltration rates and runoff volumes (Beden et al., 2023). Researchers who placed RF on highest weight in their study with RF intensity of 452 to 1020 mm/yr in Tamil Nadu (Antony Ravindran et al., 2024), 1,050 to 1,400 mm/yr in Amravati (Kathe et al., 2024), 1438 to 1603 mm/yr in Gannan China highly correlated with groundwater availability using SWAT analysis (Zhang et al., 2023), 544 to 610 mm/yr has a positive linear influence on the regional hydro-climatic patterns (Owolabi et al., 2020).

Lineament Density (LD)

Lineament represents geological structures and is considered an effective indicator because they serve as pathways for secondary permeability in the hydrogeological study (Al-Djazouli et al., 2021). Based on the review, LD contributes a weight of 7.7% from all influence factors with the largest weights. The lineament can be analyzed by SRTM data and validated using the geological maps (Kessar et al., 2020). Assessing this parameter is important especially in hard rock areas (Al-Djazouli et al., 2021), which is relatively has low permeability and porosity. The equation of lineament density can be calculated by dividing the total length of all identified lineaments by the area of the catchment under investigation.

Drainage Density (DD)

The drainage density as a stream line per unit area extracted from elevation model data contributing 7.0 % to the overall weighting plays a crucial role in assessing key hydrogeological parameters, such as infiltration and permeability (Banerjee et al., 2020; Owolabi et al., 2020; Ozegin et al., 2023). A lower drainage density improves groundwater availability due to potentially increased infiltration (Banerjee et al., 2020; Saranya & Saravanan, 2020). Impermeable subsurface material, limited vegetation, steep terrain lead to increased drainage density (Ozegin et al., 2023). DD parameter might not be prioritized due to only 15% of the total area constitutes a very high drainage density (Saravanan et al., 2020).

Multicollinearity Analysis

Prior to modelling and after influence factor selection as independen variables input, multicollinearity should be performed to evaluate relationship between each influence factors. Testing for multicollinearity is essential because it lowers the prediction accuracy of a model that relies on a linear combination of variables (B. Ghosh, 2021). Based on the review, not all researchers conduct multicollinearity testing, despite its critical importance. The most commonly used methods are Variance Inflation Factors (VIF) and Tolerance (TOL), which are widely recognized metrics for detecting multicollinearity in geoscience research. The generally accepted thresholds are a TOL value greater than 0.1 and a VIF value less than or equal to 10 (Mukherjee & Singh, 2020; Das et al., 2022; B. Ghosh, 2021; Guria et al., 2024; Ozegin et al., 2024). However, some researchers apply stricter criteria, such as a TOL value below 0.2 and a VIF value above 5, to more rigorously detect multicollinearity (Chen et al., 2018).

Model Validation Technique

In scientific analysis such as AHP, validation is one of the most essential step (S. Das, 2019; P. Saha et al., 2024). Without ground truth, the results of a groundwater potential map are essentially meaningless (B. Saha et al., 2024). The validation process determines the correlation between groundwater potential maps and field survey (Faheem et al., 2023). It is fundamental to evaluate the model's accuracy and robustness (Meng et al., 2024; B. Saha et al., 2024; P. Saha et al., 2024). Various actual data are used in the validation process (Table 2) to evaluate data such as well yield (Jothibasu & Anbazhagan, 2016; Kumar & Krishna, 2018; Murmu et al., 2019; Mukherjee & Singh, 2020; Owolabi et al., 2020; B. Ghosh, 2021; Maizi et al., 2023; Meng et al., 2024; Sikakwe et al., 2024; Twaha et al., 2024; Zhang et al., 2023; Guria et al., 2024; Mukherjee & Singh, 2020), groundwater level (D. Ghosh et al., 2020; Akbari et al., 2021; Ravichandran et al., 2022; Antony Ravindran et al., 2024; Opoku et al., 2024; B. Saha et al., 2024; Saravanan et al., 2020; Singh et al., 2024), spring (Şener et al., 2018), geophysical data such as gravity and wireline logging (Mohammed et al., 2024), and geosite as indication of water accumulation can be defined as a naturally occurring, artificially excavated, constructed, or improved underground cavity (Muavhi & Thamaga, 2023).

According to the review, most researcher has been using yield data to assess model accuracy in validation process. The data is categorized into some classes depending on based on their yield and the availability of groundwater across various seasons (D. M. Das et al., 2022) with various class terminologies, units, and classification metrics. Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC) is a commonly used standardized tool to validate and evaluate the model (P. Saha et al., 2024). It is a visual tool for assessing a model's performance, depicting the relationship between the true positive rate and the false positive rate at different threshold values for a specific variable. Each point on the curve reflects a sensitivity-specificity pair associated with a specific threshold (Meng et al., 2024; P. Saha et al., 2024). However, there are other ways to measure model’s accuracy and precision such as coefficient of determination and correlation (Owolabi et al., 2020; Aykut, 2021), Kappa co-efficient (D. Ghosh et al., 2020), etc.

The Role of Sensitivity Analysis in Addressing the Uncertainty

Model input data layers inherently contain unavoidable uncertainties due to the incomplete understanding of real-world conditions (A. Kumar & Krishna, 2018). Sensitivity analysis can identify the impact of each parameter or key influence factors (Moharir et al., 2023). Based on the review, not all studies performed sensitivity analysis, particularly those have validated the groundwater potential model and map removal, as the most commonly used approach, has been employed by several researchers to conduct sensitivity analysis and identify the most influential factors. For instance, the study in Esan Plateau, Nigeria (Ozegin et al., 2024) showed that the model's AUC = 75.45%, with rainfall identified as a highly sensitive parameter. Similarly, in coal mining-impacted terrains of India, weathered zone thickness and rainfall were found to have a positive impact on the model, with an AUC of 0.7936 and 0.7692, respectively (A. Kumar & Krishna, 2018). In another study, lithology was deemed the most influential parameter in delineating GWP with model accuracy of R^2 = 0.59 (M. Kumar et al., 2022),while slope was a crucial factor in the Kangsabati River Basin study, with an overall accuracy of 79.77% (D. Ghosh et al., 2020), and the Damoh District study, which incorporated geomorphology as a key parameter, achieved training accuracy = 82% and testing accuracy = 81%, confirming its significant role in GWPZ delineation (Moharir et al., 2023).

Conclusion

The AHP method applied in groundwater potential research has significantly increased in the last decade (2015-2024) as part of groundwater management. Researchers from diverse fields evaluated the method and deemed its effectiveness and accuracy to be satisfactory. Currently, AHP has been collaborated on and combined with other statistic and machine learning techniques in order to improve and/or compare model accuracy. According to the bibliometric and systematic review, the five influence factors were observed with significant normalized weight value, namely lithology (LT), geomorphology (GM), drainage density (DD), rainfall (RF), lineament density (LD), respectively. Researchers typically select influencing factors based on prior groundwater studies and AHP frameworks. Additionally, the collaboration of researchers within a single article indicates the use of expert judgment in the factor selection, with each contributor providing insights based on their expertise. Most researchers used well yield and groundwater level as validation data using ROC-AUC to evaluate the model.

To achieve an accurate model, multicollinearity and sensitivity analysis are essential which help eliminate redundant variables and assess the impact of each parameter, providing a deeper understanding of the study area's characteristics and improving model accuracy. However, not all studies performed both stages. The author consider that resolution data, deep understanding of the hydrogeological setting, multicollinearity analysis, validation process, and sensitivity analysis are necessary to be involved in AHP for groundwater potential assessment to reduce bias model and better understand influence factors.

However, the study has several limitations. It depends solely on the Scopus database, the exclusion of non-English publications and reliance on keyword indexing could have resulted in missing valuable studies. Future research should consider multi-database searches and cross-lingual analysis.

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