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Review

Geospatial Assessment of Water Security in Mining-Affected Watersheds: A Systematic Review of Composite Indices, Methodological Gaps, and the Proposed Mining Water Security Composite Index ICSHM

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ABSTRACT: Mining activities constitute one of the most significant anthropogenic pressures on freshwater systems worldwide, producing diverse impacts on water availability, water quality, and ecosystem integrity. Despite substantial advances in geospatial technologies, none of the assessment frameworks identified in the reviewed corpus comprehensively integrates these dimensions for mining-affected watersheds. This systematic review aimed to identify, classify, and synthesize water security indices and geospatial assessment frameworks applied to mining-affected watersheds worldwide, develop an original taxonomy describing their methodological structure, and identify the research gaps supporting the development of the Mining Water Security Composite Index ICSHM. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, systematic searches were conducted in the Web of Science, Scopus, and SciELO databases, covering the period from 2007 to 2026 (3209 initial records). Reference management and screening were performed using Zotero 7.0 and Rayyan. Data extraction was based on an original eight-category geospatial taxonomy (G1–G8) covering Geographic Information Systems (GIS) mapping, optical and radar remote sensing, distributed hydrological modeling, hydraulic and contaminant transport modeling, landscape ecology, cloud-based analytics, and spatial multi-criteria decision analysis, while methodological quality was assessed using an adapted Critical Appraisal Skills Programme (CASP)–Joanna Briggs Institute (JBI) framework. From 1847 unique records screened, 50 studies conducted across 22 countries met the inclusion criteria. The review identified two major methodological gaps. First, none of the 17 identified water security indices simultaneously incorporates the five dimensions proposed in this review for the assessment of mining-affected watersheds. Second, none of the reviewed studies integrates distributed hydrological modeling, hydraulic and contaminant transport

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modeling, and spatial multi-criteria analysis within a single assessment framework (G4 + G5 + G8 = 0%). These findings provide a strong methodological rationale for the proposed ICSHM, which is structured around five complementary dimensions: water availability, water quality, mining contamination risk, ecosystem integrity, and sociocultural vulnerability. The framework integrates geospatial methods represented by categories G1–G8 and is designed to support future validation across mining-affected watersheds with contrasting environmental and mining settings.

Keywords: Water security; Mining-affected watersheds; Geospatial assessment; Composite index; Systematic review; Watershed management; Remote sensing; Hydrological modeling; ICSHM

1. Introduction

Mining activities currently affect more than 35,000 km of river systems worldwide, with elevated sediment loads documented in at least 23% of the monitored freshwater bodies [1]. Mineral extraction generates persistent impacts on water availability, water quality, and ecosystem integrity that extend well beyond mining operation boundaries [2,3]. These impacts vary according to mining typology. Illegal artisanal mining produces chronic contamination by mercury and other heavy metals, as documented in artisanal gold-mining watersheds in the Colombian Pacific region, where more than 166,000 hectares of forest have been destroyed, and approximately 80% of sampled individuals exhibited mercury contamination [4]. In contrast, industrial mining can produce large-scale acute disturbances, exemplified by the Brumadinho tailings dam failure (January 2019), which released approximately 12 million m^3 of mine tailings, caused 270 fatalities, and contaminated more than 300 km of the river system [5].

Water security has emerged as a central organizing concept in environmental governance since the seminal work of Cook and Bakker (2012) [6]. Its operationalization through composite assessment frameworks, including the World Resources Institute (WRI) Aqueduct [7], the Global Water Security Index [8], and the UN-Water framework [9], has substantially advanced quantitative assessments at global and regional scales. However, these frameworks were developed primarily for broad territorial and sectoral comparisons and therefore lack the dimensional specificity required to capture the heterogeneous, spatially explicit impacts of mining activities on watershed hydrological systems.

Geospatial technologies provide the technical foundation for overcoming these limitations at the watershed scale. Freely available satellite imagery from Sentinel-2 and Landsat-8/9 missions, Synthetic Aperture Radar (SAR) data from Sentinel-1, and cloud-computing platforms such as Google Earth Engine [10] have greatly expanded the capacity for spatially explicit monitoring of mining impacts. Likewise, distributed hydrological models (e.g., Soil and Water Assessment Tool (SWAT)+ and Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS)) [11], hydraulic models (e.g., Hydrologic Engineering Center-River Analysis System (HEC-RAS) 2D), and GIS-based Multi-Criteria Decision Analysis (GIS-MCDA) enable the integration of physical, chemical, ecological, and socioeconomic variables into composite spatial indicators [12]. Despite these methodological advances, this review identified no systematic assessment of how these geospatial tools have been applied to evaluate water security in mining-affected watersheds. Nor did it identify any composite index that integrates these complementary methodologies into a unified framework for extractive watersheds.

This systematic review aims to identify and synthesize water security indices and geospatial assessment frameworks applied to mining-affected watersheds worldwide, characterize their methodological structure using the proposed G1–G8 taxonomy, and identify the research gaps that support the development of the Mining Water Security Composite Index ICSHM.

2. Methodology

2.1. Review Design

This study consists of a systematic literature review integrated with a descriptive bibliographic analysis of the included corpus and was conducted in strict accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [13]. Bibliographic management and automated duplicate removal were performed using Zotero 7.0 [14], whereas the systematic screening process was conducted through Rayyan [15], a web-based platform specifically designed for systematic reviews that provides transparent and traceable records of inclusion and exclusion decisions.

Although Google Scholar was initially considered a potential data source, it was subsequently excluded due to its well-documented limitations in search reproducibility and transparency [16,17]. The descriptive bibliographic analysis followed the general organizational principles proposed by Donthu et al. (2021) [18] for synthesizing publication patterns.

2.2. Research Question

The systematic review was structured using an adapted Population, Intervention, Comparison, Outcome (PICO) framework following the approach proposed by De León Pérez et al. (2024) [12] (Table 1). The review addressed the following research question:

> *"Which water security indices, composite indicators, and geospatial assessment frameworks have been applied to mining-affected watersheds worldwide? Which dimensions and geospatial methods constitute these approaches, and what methodological gaps support the development of a specific composite index for the integrated geospatial assessment of water security in extractive watersheds?"*

Table 1. Adapted PICO framework for the geospatial assessment of water security in mining-affected watersheds.

PICO Element	Operational Description
P (Population/Problem)	Watersheds worldwide are affected by mining activities of any type, including surface and groundwater systems exposed to quantifiable extractive pressures.
I (Intervention/Exposure)	Water security indices, composite indicators, assessment frameworks, and geospatial modeling tools used to characterize, monitor, or predict mining impacts on water systems.
C (Comparison)	General water security frameworks lack mining-specific components compared with frameworks specifically designed for mining-affected watersheds; studies employ explicit geospatial operationalization, whereas others lack a spatial component.
O (Outcome)	Constituent dimensions of existing water security indices; variables employed; geospatial methods classified according to the proposed G1–G8 taxonomy; and methodological gaps supporting the development of the Mining Water Security Composite Index ICSHM

2.3. Systematic Search Strategy

2.3.1. Databases and Search Coverage

Systematic searches were conducted in three bibliographic databases: Web of Science Core Collection (n = 1313), Scopus (n = 1819), and SciELO (n = 77). The rationale for selecting each database is presented in Table 2. These databases were chosen because they provide complementary coverage of environmental sciences, hydrology, geospatial modeling, and environmental engineering literature.

The search covered the period from 2007 to 2026 to capture the contemporary evolution of the water security concept, particularly following its consolidation within the international scientific literature [6], as well as the rapid advancement of geospatial technologies based on remote sensing, Geographic Information Systems (GIS), and cloud-computing platforms. Furthermore, adopting a multi-database search strategy

followed the methodological recommendations of Bramer et al. (2017) [19], who demonstrated that combining multiple bibliographic sources improves search comprehensiveness while reducing retrieval bias in systematic reviews. Systematic searches were executed during the second half of 2025. During manuscript preparation, additional records published in 2026 were identified and incorporated after assessment against the same eligibility criteria; no new database query was executed for this update.

No formal language restriction was applied during the search. The final corpus comprised studies published in English, Spanish, or Portuguese, which represent the predominant languages of scientific production in this research field.

Table 2. Bibliographic databases, selection rationale, search syntax, and number of retrieved records.

Database	Rationale for Selection	Search Syntax	Records Retrieved
Web of Science Core Collection	Comprehensive coverage of high-impact journals in environmental sciences and hydrology, rigorous indexing standards, and transparent inclusion criteria (Clarivate, 2025) [20].	TS = (Title, Abstract, Author Keywords, and Keywords Plus)	1313
Scopus	Broad coverage of Earth sciences and engineering journals, strong representation of Latin American publications, and daily database updates (Elsevier, 2025) [21].	TITLE-ABS-KEY = ((Title, Abstract, Author Keywords, and Indexed Keywords)	1819
SciELO	Specialized coverage of peer-reviewed Latin American scientific literature, including high-quality Ibero-American journals not indexed in Web of Science or Scopus (Packer et al., 2014) [22].	Adapted search terms applied to title, abstract, and keywords	77

Note: A total of 3209 records were initially retrieved. Google Scholar was excluded from the formal search protocol due to documented limitations in search reproducibility. Specifically, it does not support field-specific Boolean search strings, does not ensure temporal stability of search results, and does not provide structured, exportable metadata suitable for systematic review workflows [16,17]. SciELO was included to improve retrieval of Latin American scientific literature published in peer-reviewed journals with verifiable indexing standards [22]. Database characteristics were obtained from the official documentation of Web of Science [20], Scopus [21], and SciELO [22]. The multi-database search strategy followed the recommendations of Bramer et al. (2017) [19]. Database searches were executed during the second half of 2025, with database access and reference verification continuing into the first half of 2026.

2.3.2. Search Strings and Boolean Operators

Five structured search strings (CS1–CS5) were developed to comprehensively cover the conceptual, methodological, and applied dimensions of this review. Search String 1 (CS1) was prioritized because understanding mining typologies and their impacts on water resources represents a necessary conceptual foundation before identifying and evaluating solutions based on composite indices, assessment frameworks, geospatial modeling, and spatial analytical tools.

Subsequently, CS2–CS4 focused on retrieving literature related to water security indices, conceptual frameworks, and integrated approaches for socio-environmental assessment, whereas CS5 specifically targeted geospatial methodologies, including spatial modeling techniques, remote sensing technologies, and GIS-based analytical approaches.

Because of the operational characteristics of the SciELO database, search terms were executed as independent queries. In contrast, equivalent standardized Boolean expressions were used in the Web of Science Core Collection and Scopus, ensuring methodological consistency, comparable document retrieval, and full reproducibility of the search process (Table 3).

Table 3. Systematic search strings organized by thematic dimension, including database-specific search strategies.

Search String	Thematic Dimension	Boolean Expression (Web of Science/Scopus)	Adapted Search Terms (SciELO)
CS1	Mining typologies and differentiated impacts on water resources	("artisanal mining" OR "small-scale mining" OR "ASGM" OR "illegal mining" OR "informal mining" OR "industrial mining" OR "large-scale mining" OR "abandoned mine" OR "mine closure" OR "legacy mining" OR "tailings dam failure" OR "dam breach") AND ("water quality" OR "water contamination" OR "water security" OR "mercury" OR "acid mine drainage" OR "heavy metals" OR "sediment" OR "turbidity") AND ("watershed" OR "river basin" OR "catchment" OR "hydrological impact")	minería artesanal AND agua; mineração AND qualidade da água; minería ilegal AND contaminación; garimpo AND água AND contaminação
CS2	Water security indices for mining contexts	("water security" OR "water security index" OR "hydrological security") AND ("mining" OR "artisanal mining" OR "illegal mining" OR "tailings" OR "mine drainage") AND ("index" OR "indicator" OR "composite index" OR "framework" OR "assessment")	seguridad hídrica AND minería; segurança hídrica AND mineração; indicador hídrico AND minería
CS3	Geospatial modeling in mining-affected watersheds	("GIS" OR "remote sensing" OR "geospatial" OR "spatial analysis" OR "Google Earth Engine" OR "SWAT" OR "hydrological modeling") AND ("water quality" OR "water security" OR "water contamination") AND ("mining" OR "tailings" OR "artisanal mining")	SIG AND minería AND agua; sensoriamento remoto AND mineração AND água; modelagem hidrológica AND mineração
CS4	Global water-risk frameworks and composite indices	("water security framework" OR "water risk index" OR "Aqueduct" OR "water stress index") AND ("composite indicator" OR "multicriteria" OR "AHP" OR "weighted index" OR "MCDA")	índice de calidad del agua AND minería; vulnerabilidade hídrica AND mineração
CS5	Taxonomy of geospatial methods for mining water security assessment	("GIS" OR "remote sensing" OR "Google Earth Engine" OR "SWAT" OR "HEC-RAS" OR "InSAR" OR "Sentinel" OR "Landsat" OR "landscape ecology" OR "FRAGSTATS") AND ("water security" OR "water quality" OR "hydrological impact") AND ("mining" OR "tailings" OR "mine drainage")	SWAT AND minería AND cuenca; HEC-RAS AND mining AND river; Google Earth Engine AND mining AND water

Note: Searches were executed during the second half of 2025; the full search chronology is reported in Section 2.3.1. The search period (2007–2026) was defined to encompass the consolidation of the contemporary water security concept following the seminal contribution of Cook and Bakker (2012) [6], together with the operational expansion of second-generation satellite missions and cloud-based geospatial platforms (e.g., Gorelick et al., 2017 [10]). CS1 was prioritized because understanding the nature of mining-related impacts logically precedes the identification of methodological solutions addressed by CS2–CS5. In SciELO, search terms were executed as independent searches because the platform does not support complex Boolean expressions equivalent to those available in Web of Science and Scopus. AHP: Analytic Hierarchy Process; ASGM: Artisanal and Small-scale Gold Mining; InSAR: Interferometric Synthetic Aperture Radar.

2.4. Eligibility Criteria

Eligibility criteria were established *a priori* (Table 4) following the recommendations of Lefebvre et al. (2022) [23], adapted to the context of geospatial assessment in mining-affected watersheds. Only studies simultaneously meeting the following three core criteria were considered eligible for inclusion: (A) documented impacts on water resources; (B) a clearly defined mining context; and (C) the explicit application of at least one geospatial method. This rigorous selection strategy ensured that the final body of literature remained methodologically consistent and directly aligned with the objectives of the present systematic review. The temporal criterion was applied uniformly across the review period (2007–2026), with no additional exclusion based on publication year. A citation-count threshold for studies published before 2010 appeared in the original protocol but was not applied as an exclusion criterion, since citation

count is strongly influenced by publication age, discipline, language, and journal visibility, and is not an appropriate methodological eligibility criterion for a systematic review.

Table 4. Eligibility criteria for study inclusion and exclusion.

Criterion	Inclusion Criteria	Exclusion Criteria
Study type	Original empirical studies, previous systematic reviews, and technical reports with reproducible methodologies.	Editorials, opinion papers without empirical data, and geological exploration studies lacking water-resource assessment.
Topical relevance	Studies addressing: (1) water security indices in mining contexts; (2) geospatial modeling of mining-related impacts on water resources; or (3) spatially explicit MCDA frameworks applied to mining-affected watersheds.	Studies focusing exclusively on mineral deposits, extraction techniques, or mining economics without an environmental or hydrological component.
Geospatial component	Explicit application of at least one geospatial method, including GIS, remote sensing, distributed hydrological modeling, spatial interpolation, or landscape analysis.	Laboratory-based or point-scale water assessments without spatial representation at the watershed scale.
Mining context	Any mining typology, including industrial mining, artisanal and small-scale mining (ASM), illegal or informal mining, legacy and post-closure mining, and catastrophic mining events.	Extractive activities without documented impacts on water resources.
Spatial scale	Watershed, sub-watershed, or river-reach studies with clearly defined hydrological boundaries.	Point-scale investigations without integration into a hydrological unit.
Time period	Primary search period: 2007–2026, applied uniformly to all studies.	No additional temporal exclusion criteria.
Language	No formal language restriction was applied. The final corpus comprised studies published in English, Spanish, or Portuguese.	None.
Availability	Full-text articles accessible through institutional subscriptions or verified repositories.	Full text unavailable after author contact and a 15-day waiting period.

2.5. Study Selection Process (PRISMA 2020)

The study selection process followed the four-stage workflow recommended by the PRISMA 2020 statement (Figure 1).

During the identification stage, a total of 3209 records were retrieved from the selected bibliographic databases. Automated duplicate removal was subsequently performed using Zotero 7.0, resulting in the exclusion of 1362 duplicate records and yielding 1847 unique publications for screening.

In the screening stage, titles and abstracts were assessed by the lead reviewer on the Rayyan platform, resulting in the exclusion of 1682 records that did not meet the predefined eligibility criteria. Consequently, 165 articles were selected for full-text assessment.

During the eligibility stage, the full texts were critically evaluated using the adapted CASP–JBI quality assessment framework. This process resulted in the exclusion of an additional 115 studies, producing a final corpus of 50 articles that met all eligibility criteria and were included in the systematic review. Screening and full-text assessment were performed by the lead reviewer, with all inclusion and exclusion decisions documented in Rayyan. Because selection was carried out by a single reviewer, inter-rater agreement statistics such as Cohen's kappa were not applicable. This is acknowledged as a limitation in Section 4.4.

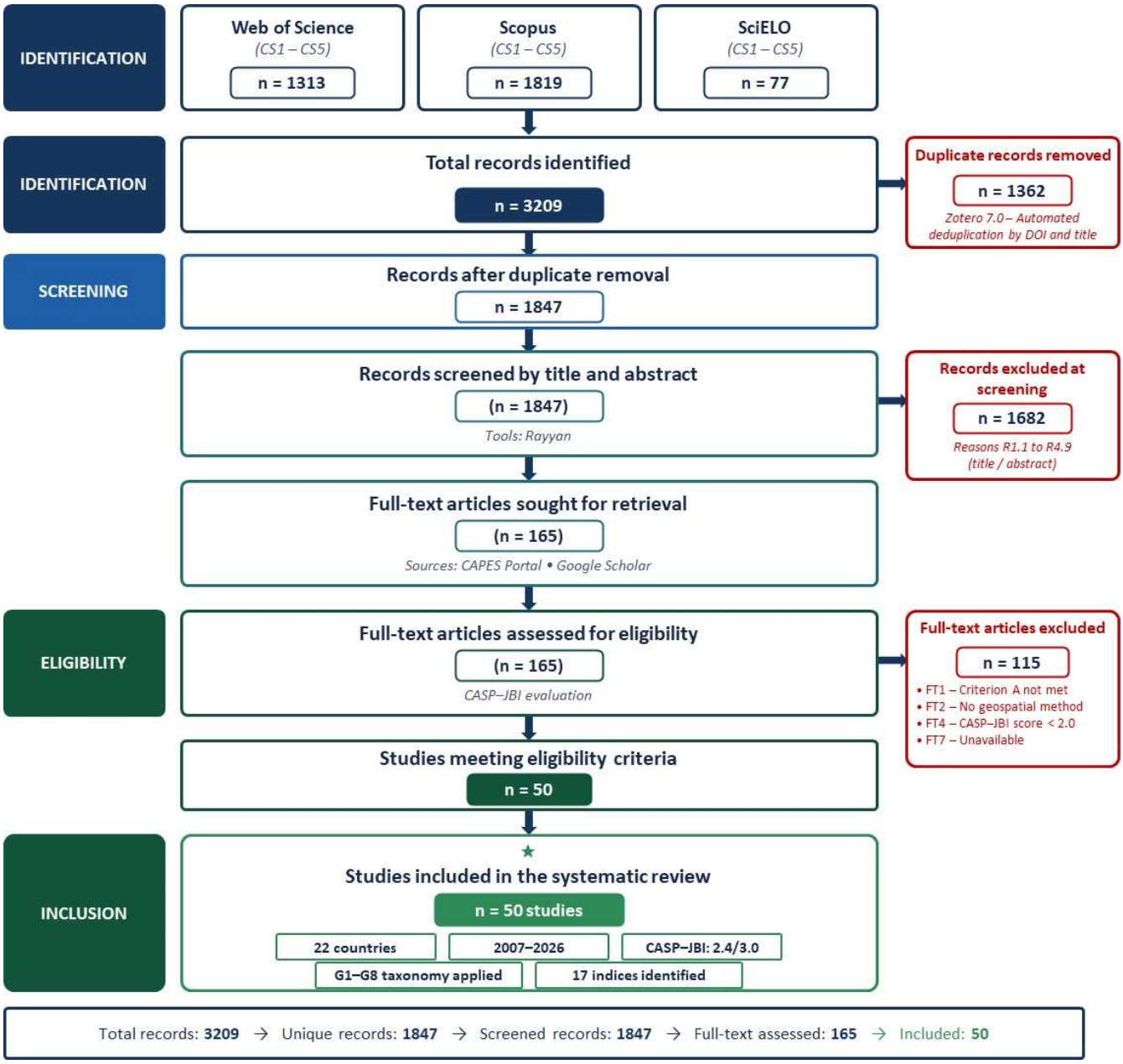


Figure 1. PRISMA 2020 flow diagram illustrating the study selection process for systematic review. Adapted from Page et al. (2021) [13], published under a Creative Commons Attribution 4.0 International License.

2.6. Taxonomy of Geospatial Methods (G1–G8)

As the principal methodological contribution of this study, we propose a novel taxonomy comprising eight categories for classifying geospatial methods used to assess water security in mining-affected watersheds. The taxonomy was developed inductively from the literature corpus and refined through informal consultation with researchers working in remote sensing, hydrological modeling, and spatial analysis. Its development followed three sequential operational criteria: (1) Instrumental differentiation: each category groups methods that share the same physical principle of geospatial data acquisition or processing while remaining functionally distinct from the other categories; (2) Relevance to mining water security: only categories with documented application in the literature on mining-related water impacts or with technically justifiable potential to assess at least one dimension of the Mining Water Security Composite Index ICSHM were included; (3) Exhaustiveness and minimal overlap: the taxonomy encompasses the entire spectrum of geospatial methodologies identified in the reviewed literature.

Categories are mutually exclusive at the method level, meaning that each individual method is assigned to only one category. However, a study may be assigned to multiple categories when it applies multiple methods, consistent with the non-exclusive classification approach reported in Tables 5.

Table 5. G1–G8 taxonomy of geospatial methods for water security assessment in mining-affected watersheds.

Cat.	Category	Representative Methods	Tools/Software	Application in Mining Contexts
G1	Vector/Raster GIS Mapping and Analysis	Map algebra, proximity analysis, IDW/Kriging interpolation, supervised classification using traditional statistical methods	ArcGIS Pro, QGIS, GRASS GIS, Surfer	Mapping of mining operations, areas of influence, contaminant distribution
G2	Optical Multispectral Remote Sensing	NDVI, NDWI and NDTI indices; surface reflectance; temporal change detection	Sentinel-2, Landsat-8/9, MODIS, ASTER, SPOT	Surface turbidity assessment, riparian vegetation loss, expansion of mining operations
G3	Radar Remote Sensing (SAR/InSAR)	SAR backscatter, differential interferometry (InSAR), temporal coherence analysis	Sentinel-1, ALOS-2, TerraSAR-X, IfSAR	Detection of illegal mining under cloud cover, land subsidence, tailings dam monitoring
G4	Distributed Hydrological Modeling	Spatial water balance, runoff simulation, groundwater recharge estimation	SWAT+, HEC-HMS, VIC, TOPMODEL, USLE	Streamflow alteration, watershed water balance, diffuse contaminant loading
G5	Hydraulic and Contaminant Transport Modeling	River hydraulics, contaminant dispersion, hydrodynamic simulation	HEC-RAS 2D, FLO-2D, CE-QUAL-W2, MODFLOW-MT3D, HEC-HMS	Tailings plume dispersion, dam-failure simulation, sediment and contaminant transport
G6	Landscape Ecology Analysis	Fragmentation metrics, habitat connectivity, land use/land cover (LULC) change, ecosystem service assessment	FRAGSTATS, Guidos Toolbox, InVEST, TerrSet	Riparian vegetation fragmentation, hydrological connectivity, land-cover monitoring
G7	Cloud-Based Geospatial Analytics and Machine Learning	Satellite time-series analysis, machine learning classification, environmental big-data analytics	Google Earth Engine, Microsoft Planetary Computer, Python/R (XGBoost, Random Forest, SVM)	Continuous turbidity monitoring, automated mining detection, multi-decadal environmental analysis
G8	Spatial Multi-Criteria Decision Analysis (GIS-MCDA)	Spatial AHP, geospatial TOPSIS, weighted composite indices, fuzzy GIS	ArcGIS + SuperDecisions, QGIS + Python, R-spatial	Composite water-risk indices, watershed vulnerability mapping—Methodological foundation of the proposed ICSHM

Note: Some tools appear in more than one category because their classification depends on the analytical objective rather than on the software itself. HEC-HMS, for example, supports both watershed water balance simulation (G4) and flood routing coupled with water quality modules (G5). The decision rules applied to resolve these cases are described in the following paragraph. ALOS-2: Advanced Land Observing Satellite-2; ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer; GRASS: Geographic Resources Analysis Support System; IDW: Inverse Distance Weighting; InVEST: Integrated Valuation of Ecosystem Services and Trade-offs; MODIS: Moderate Resolution Imaging Spectroradiometer; NDTI: Normalized Difference Turbidity Index; NDVI: Normalized Difference Vegetation Index; NDWI: Normalized Difference Water Index; SPOT: Satellite pour l'Observation de la Terre; SVM: Support Vector Machine; TOPMODEL: TOPography-based hydrological MODEL; TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution; USLE: Universal Soil Loss Equation; VIC: Variable Infiltration Capacity; XGBoost: Extreme Gradient Boosting.

To ensure consistent coding and address potential overlap between categories, explicit decision rules were applied during data extraction. When a study employed Google Earth Engine, classification was determined by the primary analytical objective: studies using the platform for time-series optical spectral analysis were coded as G2, whereas those applying machine-learning classification algorithms such as Random Forest or XGBoost as the primary method were coded as G7. HEC-HMS was classified under G4 when used for watershed water balance and runoff simulation, and under G5 when configured for flood

routing or coupled with water quality modules. Supervised classification using traditional statistical methods such as maximum likelihood was assigned to G1, while automated classification using deep learning or ensemble machine learning algorithms was assigned to G7. Studies integrating methods across multiple categories were assigned to all applicable categories.

This consultation was informal: the category definitions and the decision rules described above were discussed with colleagues working in these three areas, and their comments were incorporated into the final version of the taxonomy. No structured validation protocol, formal consensus procedure or inter-rater agreement statistic was applied. The G1–G8 taxonomy should therefore be understood as internally consistent and specific to this domain rather than externally validated, a limitation acknowledged in Section 4.4.

2.7. Data Extraction

Data extraction was conducted using two complementary structured data extraction forms. The first form was designed to support the screening and eligibility assessment of the retrieved studies, whereas the second was used to conduct detailed extraction and systematic organization of study characteristics across four thematic blocks.

Block A comprised the bibliographic identification of the selected publications. Block B focused on the characterization of mining activities and mining typologies investigated in each study. Block C addressed the dimensions, variables, and indicators associated with water security indices and broader socio-environmental assessment frameworks. Finally, Block D incorporated the geospatial methodological component, systematically organized according to the proposed G1–G8 taxonomy.

Both data extraction forms were implemented and managed using structured Microsoft Excel workbooks to ensure consistency, traceability, and standardized data recording throughout the review process.

2.8. Methodological Quality Assessment (CASP–JBI)

The methodological quality of the included studies was assessed using an adapted CASP–JBI appraisal tool [24,25] (Table 6), comprising five evaluation dimensions scored on a three-point scale (1–3). A mean score of ≥2.0 out of 3.0 was established as the eligibility threshold, corresponding to the minimum level of verifiable moderate methodological quality. Studies with mean scores below 2.0 were excluded from the review. In practice, all studies in the final corpus exceeded this threshold. The adaptation was specifically designed to address the methodological characteristics of geospatial environmental assessment studies, which are not fully captured by the original CASP or JBI appraisal instruments.

Table 6. Adapted CASP–JBI appraisal tool for methodological quality assessment of geospatial environmental assessment studies.

Code	Assessment Dimension	Operational Description	Scoring
C1	Clarity of Research Objectives	Clearly defines the environmental or water-related problem, research question, and spatial scope. Includes explicit delineation of the study area and its hydrological context.	1 = Weak 2 = Moderate 3 = Strong
C2	Rigor of Study Area Delineation	Provides sufficient spatial, climatic, hydrological, and ecological information. Delineates the watershed using explicit and well-justified criteria.	1 = Weak 2 = Moderate 3 = Strong
C3	Appropriateness of Geospatial Methods	Selects and justifies suitable geospatial methods; specifies spatial and temporal resolution; acknowledges the technical limitations of the selected tools.	1 = Weak 2 = Moderate 3 = Strong
C4	Consistency Between Results and Conclusions	Conclusions are directly supported by spatial analysis results, avoid unsupported generalizations, and quantify uncertainty whenever possible.	1 = Weak 2 = Moderate 3 = Strong

C5	Transparency of Study Limitations	Explicitly acknowledges limitations related to spatial scale, spatial resolution, data availability, and validation procedures, providing sufficient information to ensure reproducibility.	1 = Weak 2 = Moderate 3 = Strong

Note: The overall mean quality score of the reviewed studies was 2.4/3.0. The inclusion threshold was established at ≥2.0/3.0. The highest-rated dimension was C1 (Clarity of Research Objectives; mean = 2.8), while the lowest-rated dimension was C5 (Transparency of Study Limitations; mean = 2.1). The inclusion threshold of 2.0/3.0 corresponds to the minimum level of moderate methodological quality and is consistent with systematic reviews addressing comparable topics in geospatial environmental assessment (De León Pérez et al., 2024 [12]).

The instrument was developed by adapting the CASP and JBI appraisal tools to the methodological characteristics of geospatial environmental assessment studies. The five dimensions were selected to reflect the core requirements of this field: clarity of research objectives, rigour of study area delineation, appropriateness of the geospatial methods, consistency between results and conclusions, and transparency of study limitations. Each item was weighted equally, and the overall score was calculated as the arithmetic mean of the five dimensions. Quality assessment was performed by the lead reviewer; because a single reviewer applied the instrument, formal inter-rater reliability statistics were not calculated. This is acknowledged as a limitation in Section 4.4.

2.9. Evidence Synthesis

Because substantial methodological heterogeneity was identified among the included studies, precluding the application of a quantitative meta-analysis, the evidence was synthesized using a two-level thematic synthesis approach following the methodology proposed by Thomas and Harden (2008) [26]. The heterogeneity involved differences in study design, geospatial methodologies, spatial scales, environmental variables, and outcome measures, making statistical pooling inappropriate.

At the first level, a quantitative descriptive synthesis was conducted to examine the frequency, distribution, and methodological combinations associated with the proposed G1–G8 geospatial taxonomy. This analysis enabled the identification of dominant methodological trends and the prevalence of specific geospatial approaches within the reviewed literature.

At the second level, a qualitative interpretative synthesis was performed to identify emerging patterns, conceptual convergences, and methodological gaps across the selected studies. This complementary approach facilitated the integration of heterogeneous evidence and provided a comprehensive understanding of current methodological practices in studies addressing mining impacts, water security, and geospatial assessment.

3. Results

3.1. Descriptive Bibliographic Overview of the Literature Corpus

The systematic search identified 3209 records across the three selected databases (Web of Science Core Collection: 1313; Scopus: 1819; SciELO: 77). After the removal of 1362 duplicate records using Zotero 7.0, 1847 unique records remained for screening. During the screening process, 1682 records were excluded based on titles and abstracts, while an additional 115 studies were excluded after full-text assessment. In total, 1797 records were excluded, resulting in a final corpus of 50 studies originating from 22 countries, corresponding to an overall inclusion rate of 2.7% of the 1847 unique records screened. The temporal distribution of the selected studies revealed a progressive increase in scientific production over the study period (Figure 2). Publications were distributed as follows: 2007–2015 (n = 9; 18%), 2016–2020 (n = 11; 22%), 2021–2023 (n = 6; 12%), and 2024–2026 (n = 24; 48%); annualized publication rates reinforce this trend: 1.0 studies/year during 2007–2015, 2.2/year during 2016–2020, 2.0/year during 2021–2023, and 8.0/year during 2024–2026. Nearly half of the included studies (48%) were published during the most

recent period (2024–2026), indicating a marked acceleration of research interest in geospatial approaches to water security assessment in mining-affected watersheds. The reviewed literature encompassed studies conducted in 22 countries, with Brazil showing the highest representation (*n* = 11; 22%), followed by China (*n* = 8; 16%), the United States (*n* = 5; 10%), Spain (*n* = 4; 8%), India (*n* = 3; 6%), and Colombia (*n* = 3; 6%) (Figure 3).

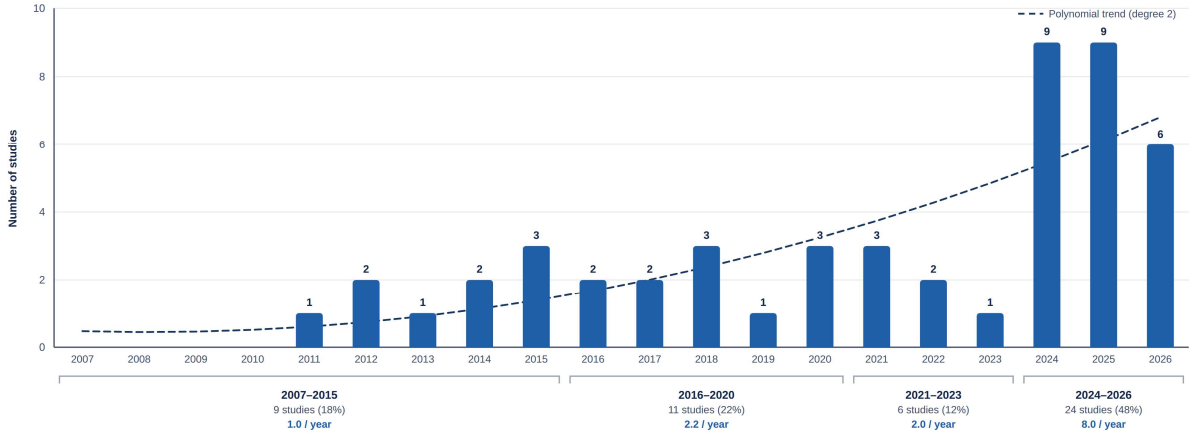


Figure 2. Temporal distribution of the 50 studies included in the systematic review (2007–2026). Annualized publication rates: 2007–2015 (1.0/year), 2016–2020 (2.2/year), 2021–2023 (2.0/year), 2024–2026 (8.0/year); rates are reported beneath each period to allow a fair comparison across intervals of different length. No study published between 2007 and 2010 met the eligibility criteria; the earliest included study dates from 2011. The dashed line represents a second-degree polynomial trend. Although the period 2024–2026 accounts for only 15% of the overall study period, it comprises 48% of the studies included in the review, highlighting the rapid growth and increasing scientific interest in geospatial approaches to water security assessment in mining-affected watersheds. Source: authors' elaboration.

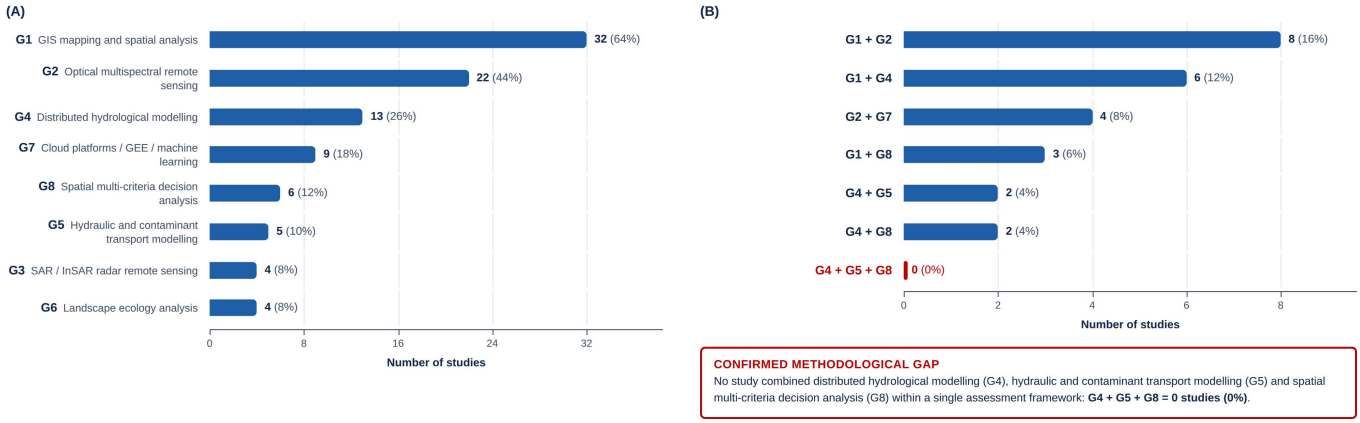


Figure 3. Distribution of the reviewed corpus according to the G1–G8 geospatial taxonomy (*n* = 50 studies). (**A**) Frequency with which each category of the taxonomy was applied across the 50 included studies; a single study may employ multiple categories, so percentages do not sum to 100%. (**B**) Frequency of the methodological combinations identified; 35 studies (70%) applied a single category and 15 (30%) combined two or more, and because the combinations are not mutually exclusive their counts do not partition the corpus. The highlighted methodological gap corresponds to the complete absence of studies integrating distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8) within a single assessment framework (G4 + G5 + G8 = 0 studies; 0%). Source: authors' elaboration.

3.2. Mining Typologies

The reviewed literature encompassed six major mining typologies: coal mining (*n* = 14; 28%), gold mining (*n* = 11; 22%), iron mining (*n* = 8; 16%), multiple heavy-metal mining (*n* = 7; 14%), metal sulfide mining (*n* = 4; 8%), and other mining typologies (*n* = 6; 12%).

Regarding operational scale and mining context, large-scale industrial mining represented the largest proportion of the reviewed studies (n = 22; 44%), followed by artisanal and small-scale mining (ASM) (n = 8; 16%) and studies with a mixed or unspecified operational context (n = 8; 16%), legacy and post-closure mining (n = 7; 14%), and documented catastrophic mining events (n = 5; 10%) (Figure 4).

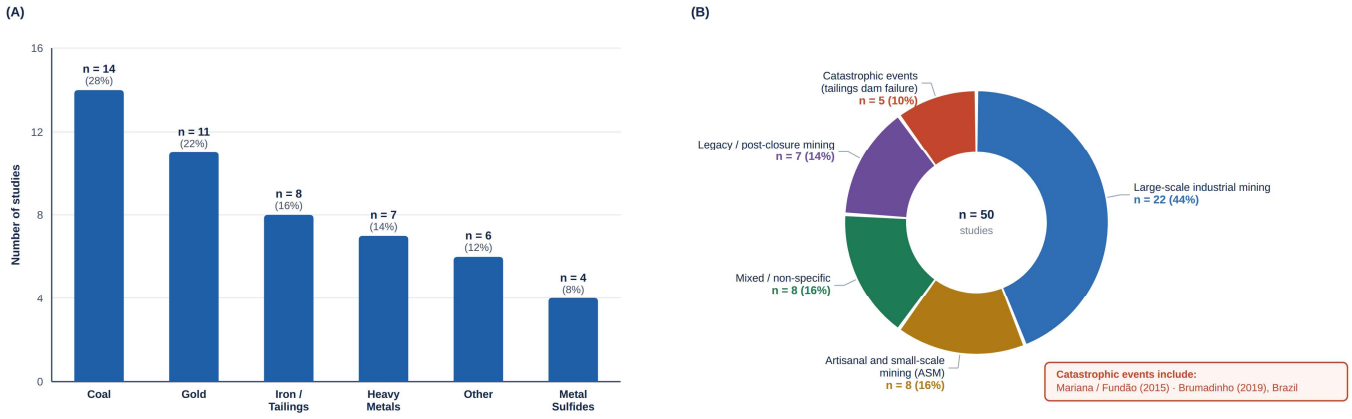


Figure 4. Distribution of mining typologies represented in the reviewed literature (n = 50 studies). (**A**) Distribution of studies by the primary mineral extracted or mining type; the categories are mutually exclusive and sum to the 50 included studies. (**B**) Distribution of the same studies by operational context. Catastrophic events include major tailings dam failures (Fundão/Mariana, 2015, and Brumadinho, 2019, Brazil). Artisanal and small-scale mining (ASM) includes artisanal, small-scale, informal and illegal mining activities, typically characterized by the absence of engineered tailings storage facilities. Mixed/non-specific comprises studies that did not report the operational scale of the mining activity, or that addressed more than one operational context without distinguishing between them. Source: authors' elaboration.

3.3. Classification According to the G1–G8 Taxonomy

Application of the proposed G1–G8 taxonomy revealed a markedly uneven distribution of geospatial methods across the reviewed literature (Table 7). GIS mapping and spatial analysis (G1) was the most frequently applied category (n = 32; 64%), followed by optical multispectral remote sensing (G2) (n = 22; 44%), distributed hydrological modeling (G4) (n = 13; 26%), cloud-based geospatial platforms and machine learning (G7) (n = 9; 18%), spatial multi-criteria decision analysis (GIS-MCDA; G8) (n = 6; 12%), hydraulic and contaminant transport modeling (G5) (n = 5; 10%), SAR/InSAR radar remote sensing (G3) (n = 4; 8%), and landscape ecology analysis (G6) (n = 4; 8%).

Table 7. Distribution of the 50 reviewed studies according to the proposed G1–G8 geospatial taxonomy.

Category	Description	*n*	%	Representative Studies
G1	GIS Mapping and Spatial Analysis	32	64%	[27–33]
G2	Optical Multispectral Remote Sensing	22	44%	[34–38]
G4	Distributed Hydrological Modeling	13	26%	[39–43]
G7	Cloud-Based Geospatial Platforms/Google Earth Engine/Machine Learning	9	18%	[44–47]
G8	Spatial Multi-Criteria Decision Analysis (GIS-MCDA/AHP)	6	12%	[27,31,48]
G5	Hydraulic and Contaminant Transport Modeling	5	10%	[33,49,50]
G3	SAR/InSAR Radar Remote Sensing	4	8%	[49,51,52]
G6	Landscape Ecology Analysis	4	8%	[46,53]

Note: A single study may be classified into multiple geospatial categories; therefore, percentages do not sum to 100%. Confirmed methodological gap: none of the 50 included studies integrated the combination of distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8) (G4 + G5 + G8 = 0 studies; 0%).

Most studies (70%, n = 35) relied on a single geospatial category, indicating limited methodological integration among geospatial approaches for assessing water security in mining-affected watersheds.

3.4. Analysis of Methodological Combinations and Identification of Research Gaps

Among the 50 studies included in the systematic review, only 15 (30%) integrated two or more geospatial categories. The most frequently identified methodological combinations were G1 + G2 (n = 8; 16%), followed by G1 + G4 (n = 6; 12%), G2 + G7 (n = 4; 8%), G1 + G8 (n = 3; 6%), and G4 + G5 and G4 + G8 (n = 2 each; 4%). Because a study applying three or more categories is counted in more than one pair, these combination counts do not partition the 15 studies.

The combination comprising distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8) was completely absent from the 50 included studies (0 studies; 0%). None of the studies in the final corpus incorporated this integrated methodological framework.

This finding provides direct empirical support for the methodological rationale underlying the development of the proposed Mining Water Security Composite Index ICSHM.

3.5. Analysis of the Identified Indices

Among the 50 studies included in the systematic review, only 17 (34%) developed or applied quantitative indices related to environmental or water-resource assessment in mining contexts. However, none proposed an integrated water security index specifically designed for mining-affected watersheds (Table 8).

For the purposes of this review, an index was recorded in Table 8 when it constituted a quantitative instrument applied at the watershed or sub-watershed scale to characterise water resource conditions or their degradation in a mining context. The instruments retained under this rule are not all of the same kind. Heavy-metal contamination indices and groundwater vulnerability indices are composite in the strict sense, aggregating two or more individual indicators into a single score. Event-monitoring indicators, by contrast, include single-variable metrics such as Modified Normalized Difference Water Index (MNDWI) or FRAGSTATS-derived landscape metrics, applied as assessment instruments within a broader environmental evaluation. The three categories are therefore reported separately in Table 8 and are not treated as equivalent.

The identified indices were grouped into three major categories. The first comprised heavy metal contamination indices, representing the most frequent category with eight studies (47%). This group included widely adopted indicators such as the Heavy Metal Pollution Index (HPI), Heavy Metal Evaluation Index (HEI), Pollution Load Index (PLI), and the Geoaccumulation Index (Igeo), all commonly used to assess environmental contamination and pollution risk.

The second category consisted of groundwater vulnerability indices, identified in three studies (18%), including established methodologies such as Depth to water, net Recharge, Aquifer media, Soil media, Topography, Impact of the vadose zone, hydraulic Conductivity (DRASTIC), Groundwater hydraulic confinement, Overlying strata, Depth to groundwater table (GOD), Pollutant Origin, Surcharge Hydraulically (POSH), and Groundwater Potential Zone (GWPZ), which are designed to evaluate aquifer susceptibility to groundwater contamination and hydrogeological risk.

The third category comprised indices for monitoring specific environmental events, identified in six studies (35%), primarily associated with mining failures, extreme events, or localized environmental degradation processes.

Overall, the reviewed literature remains dominated by fragmented, sector-specific assessment approaches, while integrated methodological frameworks remain largely absent. This fragmentation is clearly evidenced by two key findings: (i) no study integrated the methodological combination of distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8); and (ii) none of the 17 identified indices simultaneously incorporates

the five dimensions proposed in this review for the assessment of mining-affected watersheds. Together, these findings constitute the double methodological and conceptual gap that underpins the development of the proposed Mining Water Security Composite Index ICSHM.

Table 8. Typological classification of the 17 indices identified in the reviewed literature.

Index Category	*n* (%)	Index Names	Representative Studies
Heavy Metal Contamination Indices	8 (47%)	HPI, HEI, PLI, Igeo, CD, Er	[54–60]
Groundwater Vulnerability Indices	3 (18%)	DRASTIC, GOD, POSH, GWPZ	[27,31,61]
Specific Event Monitoring Indices	6 (35%)	WTPRA, Multi-impact Index, Trophic Index, MNDWI, Subsidence Index, FRAGSTATS-based Metrics	[28,44,46,48,62,63]

Note: None of the 17 identified indices integrate the five dimensions proposed in this review into a single composite index specifically designed for mining-affected watersheds. CD: Degree of Contamination; Er: Potential Ecological Risk Factor; WTPRA: Watershed-scale Tailings-pond Pollution Risk Analysis

3.6. Methodological Quality Assessment

Application of the adapted CASP–JBI appraisal tool yielded an overall mean methodological quality score of 2.4/3.0 for the reviewed corpus. The highest-rated dimension was C1 (Clarity of Research Objectives), with a mean score of 2.8, whereas the lowest-rated dimension was C5 (Transparency of Study Limitations), with a mean score of 2.1. This result reflects the frequent underreporting of methodological limitations related to spatial resolution, data availability, and validation procedures in geospatial studies of mining impacts, particularly those based on remote sensing [64].

All included studies exceeded the predefined methodological quality threshold of 2.0/3.0, thereby meeting the eligibility criteria established for this systematic review.

4. Discussion

4.1. Mining as a Structural Water Security Challenge

The findings of this systematic review should be interpreted within the context of a structural reality consistently documented in scientific literature: mining activities do not generate a single, homogeneous type of impact on water systems. Instead, they produce a wide range of differentiated pressures whose magnitude, spatial extent, propagation dynamics, and temporal persistence depend fundamentally on the mining typology, technological level, and degree of institutional formalization of the extractive activity [2,6]. This structural heterogeneity is not merely a characteristic of mining-related impacts; it is their defining feature.

Illegal and artisanal gold mining, for example, generates chronic, diffuse contamination with mercury and suspended sediments across multiple locations within the same watershed. These dispersed sources produce cumulative impacts that cannot be explained by any single mining operation, collectively degrading water availability, water quality, and ecosystem functioning. This pattern has been extensively documented in the Atrato River basin in Colombia [4,5] and the Tapajós River basin in the Brazilian Amazon [34].

In contrast, large-scale industrial mining is characterized by highly concentrated disturbances with the potential for catastrophic consequences. The collapse of the B1 tailings dam at Brumadinho (Brazil) in January 2019 released approximately 12 million m^3 of mine tailings into the Paraopeba River watershed within a matter of hours. The resulting contamination plume extended for more than 300 km in only a few days, while hydrochemical impacts documented through satellite time-series analyses by Rudorff et al. (2018) [35] and De Salis et al. (2026) [44] have persisted for several years after the disaster.

Legacy and post-closure mining represent a third category of mining pressure, characterized by delayed and persistent environmental impacts. Acid Mine Drainage (AMD) and the leaching of mine tailings may continue to impair water quality for decades after mining operations have ceased [65]. Hyperspectral remote sensing has been applied to map the spatial extent of such acidic waters in affected rivers, showing that the footprint of mine drainage can be monitored directly rather than only inferred from modelling [66]. Together, these contrasting mining typologies illustrate the broad spectrum of hydrological pressures affecting mining-affected watersheds and help explain why none of the geospatial assessment frameworks identified in the reviewed corpus adequately captures their full environmental complexity.

A second and equally important limitation concerns the conceptual dimensions incorporated into existing water security frameworks. Widely adopted global frameworks, including WRI Aqueduct [7], the Global Water Security Index [8], and groundwater vulnerability models such as DRASTIC, were originally developed to evaluate generalized water-related pressures rather than the specific environmental challenges associated with mining. Consequently, they do not explicitly account for risks associated with Acid Mine Drainage (AMD), fail to incorporate the vulnerability of communities directly dependent on mining-affected water resources, and do not integrate distributed hydrological modeling with spatial multi-criteria decision analysis. This limitation is reflected directly in the findings of the present review: none of the 17 identified indices simultaneously incorporates the five dimensions proposed in this review for the comprehensive assessment of water security in mining-affected watersheds.

These findings demonstrate that the challenge is not merely the absence of an additional water security indicator, but rather the absence of an integrated conceptual and methodological framework that can simultaneously represent hydrological processes, contaminant transport, ecosystem integrity, and the vulnerability of mining-dependent communities. This gap provides the conceptual foundation for the proposed Mining Water Security Composite Index ICSHM.

4.2. Geospatial Fragmentation as Empirical Evidence of the Methodological Gap

If the conceptual gap defines what remains absent from the current literature, the distribution of the proposed G1–G8 taxonomy explains why this absence persists. Seventy percent of the reviewed studies (n = 35) relied exclusively on a single geospatial category, revealing a scientific landscape characterized by pronounced methodological fragmentation [18].

The simultaneous integration of distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8) represents the minimum methodological framework required to develop a composite index capable of combining hydrological processes, spatially explicit contaminant transport, and multi-criteria decision support. None of these methodological categories, however, is capable of providing such functionality when applied in isolation [27,39,49].

Studies based on optical remote sensing (G2; 44%) typically provide rapid and visually intuitive assessments of surface turbidity, mining expansion, and land-cover change. Studies employing distributed hydrological modeling (G4; 26%) generate quantitative estimates of watershed water balance that meet the methodological standards expected by hydrological journals. Likewise, studies based on spatial multi-criteria decision analysis (G8; 12%) produce vulnerability maps that support territorial planning and environmental management. Each of these approaches represents a scientifically robust and valuable contribution within its own disciplinary context. Nevertheless, none of them, individually, can answer the fundamental question underlying water security assessment:

> *"To what extent is a mining-affected watershed truly water-secure across all dimensions relevant to both ecosystems and the human communities that depend upon them?"*

A comparison with other interdisciplinary assessment fields further illustrates this limitation. In food security research, the development of the Food Insecurity Experience Scale (FIES) required the explicit integration of psychometric, nutritional, and socioeconomic dimensions into a single validated assessment framework [67]. Similarly, urban seismic risk assessment platforms such as OpenQuake integrate physical hazard modeling, structural vulnerability functions, and population exposure within a unified analytical architecture [68]. In both cases, methodological progress was achieved not by simply combining existing tools, but by designing entirely new conceptual frameworks. The current state of geospatial water security assessment for mining-affected watersheds closely resembles the pre-integration stage of these disciplines: technically mature methods are available, yet they remain confined to disciplinary silos and lack an overarching conceptual architecture to integrate them into a coherent assessment framework.

The pronounced increase in scientific production observed during 2024–2026, which accounts for 48% of the reviewed corpus compared with only 18% during 2007–2015, does not contradict this interpretation. On the contrary, it reinforces its structural significance. In research fields characterized by strong methodological fragmentation, rapid growth in publication output often promotes increasing thematic specialization rather than spontaneous conceptual integration. Consequently, the present moment represents a critical stage for establishing foundational methodological frameworks capable of guiding the future development of integrated approaches. If current publication trends continue, future scientific production will likely remain concentrated in the already dominant categories (G1 and G2), whereas categories with greater integrative potential (G5, G6, and G8) may continue to be comparatively underrepresented. Under this scenario, the absence of integrative conceptual frameworks such as the proposed Mining Water Security Composite Index ICSHM would not only limit methodological convergence within the field but also constrain the development of spatially robust and operationally transferable indicators for assessing water security in mining-affected watersheds. The proposed ICSHM should be understood not merely as an additional composite indicator, but as an integrative methodological framework designed to bridge both the conceptual and methodological gaps identified throughout this systematic review.

4.3. The ICSHM as an Integrative Response to the Double Gap

The proposed Mining Water Security Composite Index ICSHM differs from the 17 indices identified in the reviewed literature not because of its mathematical formulation, but because of three fundamental design decisions that directly address the conceptual and methodological gaps documented throughout this systematic review (Figure 5).

The ICSHM addresses these shortcomings through a five-dimensional conceptual architecture (Table 9), in which each dimension responds not only to a gap identified in the reviewed literature but also to a specific impact mechanism consistently documented in studies of mining-related water security.

Water Availability (D1), operationalized through distributed hydrological modeling (G4), addresses the well-documented alteration of watershed water balances caused by mining-induced subsidence, groundwater drainage, and modifications of natural flow networks, as reported by Wan et al. (2013) [39] and Shinde et al. (2017) [40].

Water Quality (D2), implemented through the integration of GIS (G1) and optical remote sensing (G2), formalizes the extensive evidence demonstrating the effectiveness of Landsat and Sentinel-2 time series for monitoring the spatial and temporal dynamics of surface-water contamination [34,35].

Mining Contamination Risk (D3), based on the integration of radar remote sensing (G3), distributed hydrological modeling (G4), and hydraulic and contaminant transport modeling (G5), addresses the need for continuous environmental monitoring in watersheds characterized by persistent cloud cover, such as the Atrato River basin, where optical satellite imagery is available for less than 20% of the time [69].

The inclusion of G5 in this dimension is deliberate. Contaminant transport modelling is what allows D3 to represent the dispersion of tailings plumes and the downstream propagation of contamination, and it

is precisely the component whose absence from the reviewed corpus, in combination with G4 and G8, constitutes the methodological gap reported in Section 3.4.



Figure 5. Double methodological and conceptual gap identified in the reviewed corpus (n = 50 studies) and the integrative response proposed by the ICSHM. Percentages were calculated from the reviewed corpus; the bars in the first and last rows represent a confirmed absence (0%). The architectural response to arbitrary weighting addresses the concerns raised by Hofste et al. (2019) [7]. AHP = Analytic Hierarchy Process; MCDA = Multi-Criteria Decision Analysis; NDVI = Normalized Difference Vegetation Index; $Q_{7,10}$ = seven-day low flow with a ten-year return period; G1–G8 = taxonomy of geospatial methods proposed in this review; D1–D5 = the five dimensions of the ICSHM. Source: authors' elaboration.

Ecosystem Integrity (D4), operationalized through the integration of optical remote sensing (G2) and landscape ecology analysis (G6), responds to the near absence of landscape ecological metrics within the reviewed corpus (8%), despite their recognized importance for evaluating riparian ecosystem condition and ecological connectivity.

Finally, Sociocultural Vulnerability (D5), based on the integration of GIS (G1) and spatial multi-criteria decision analysis (G8), extends conventional GIS-MCDA approaches by explicitly incorporating governance indicators, ethnic territories, differential access to water resources, and other socio-environmental variables relevant to mining-affected communities [6]. The five dimensions can be stated in practical terms. D1, Water Availability, asks how much water the watershed still has: mining alters this through subsidence, groundwater drainage and the modification of natural flow networks, and the dimension captures it through mean annual streamflow, hydrological variability, groundwater recharge and the water abstraction ratio. D2, Water Quality, describes the present physical and chemical condition of surface and groundwater turbidity, total suspended solids, metal concentrations, pH and dissolved oxygen, and is the condition most frequently assessed in the reviewed corpus. D3, Mining Contamination Risk, is not a measurement of current conditions but an estimate of where contamination is likely to travel: it combines the density of mining operations, their proximity to the drainage network, the probability of acid mine drainage and the volume of stored tailings. D4, Ecosystem Integrity, measures whether riparian systems can still perform their hydrological functions, through riparian NDVI, land-cover change, habitat connectivity and minimum ecological flow. D5, Sociocultural Vulnerability, turns to the people: the population exposed, the ethnic territories affected, water supply coverage, food security and the environmental conflicts already documented in the basin.

The type of modelling each dimension requires follows from this. D1 needs distributed hydrological modelling (G4) to close the water balance. D3 needs hydraulic and contaminant transport modelling (G5) to simulate plume dispersion and dam-break propagation. D5 needs spatial multi-criteria analysis (G8) to

aggregate variables that share no common physical unit. These three are precisely the combination absent from all 50 reviewed studies, which is why the framework cannot be assembled from any single existing approach.

The possibility that an index of this kind already exists outside the retrieved corpus was examined through a targeted check of the water-security and composite-indicator literature beyond the three databases searched for this review. No instrument was found that integrates the five dimensions availability, quality, contamination risk, ecosystem integrity, and sociocultural vulnerability with distributed hydrological modelling, hydraulic and contaminant transport modelling, and spatial multi-criteria aggregation within a single framework for mining-affected watersheds. The closest antecedents fall into three groups. The first comprises multi-indicator frameworks for general water stress that cover two or three of the five dimensions, such as WRI Aqueduct [7] and the Global Water Security Index [8]. The second comprises water-quality composite indices applied to mining contexts, such as the HPI and the Water Quality Index (WQI) variants reported in Table 8, which aggregate chemical parameters without integrating hydrological process modelling. The third comprises coupled catchment models that simulate hydrological and water-quality processes but do not produce a composite score across multiple dimensions of water security. This check is reported as a verification of the identified gap and not as a second systematic review; the absence of a formal search protocol for it is acknowledged in Section 4.4.

Based on this double gap, the ICSHM was structured as a five-dimensional framework integrating hydrological, water-quality, contamination-risk, ecosystem-integrity, and sociocultural-vulnerability components (Figure 6; Table 9).

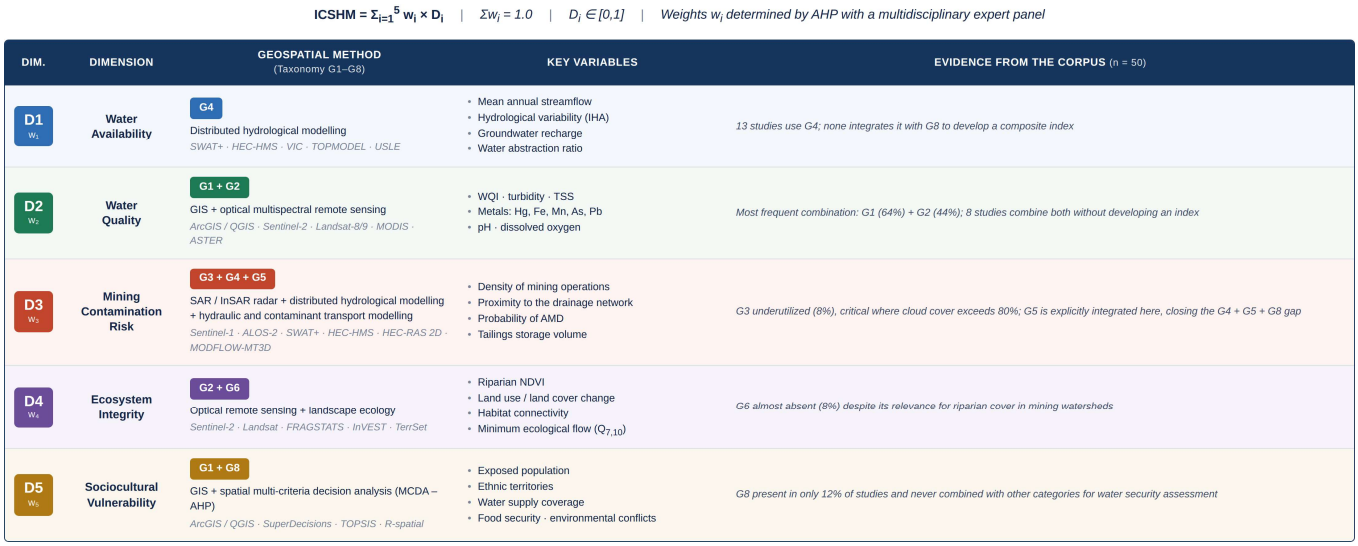


Figure 6. Conceptual framework of the ICSHM, illustrating the five assessment dimensions (D1–D5), the integrated geospatial methods (G1–G8), key variables, and supporting evidence from the reviewed corpus (n = 50 studies). D2 and D4 both draw on optical remote sensing (G2) for analytically distinct purposes: D2 captures the observable physicochemical state of the water, whereas D4 evaluates the structural capacity of the ecosystem to sustain that state over time. This separation operationalizes the cause-and-effect relationship between ecosystem integrity and water quality (Grey & Sadoff, 2007 [2]; Cook & Bakker, 2012 [6]). AHP = Analytic Hierarchy Process; AMD = Acid Mine Drainage; IHA = Indicators of Hydrologic Alteration; MCDA = Multi-Criteria Decision Analysis; NDVI = Normalized Difference Vegetation Index; $Q_{7,10}$ = seven-day low flow with a ten-year return period; TSS = Total Suspended Solids; WQI = Water Quality Index. The proposed ICSHM and the G1–G8 geospatial taxonomy constitute the original methodological contributions of this study. Source: authors' elaboration.

The mathematical formulation of the ICSHM = $\Sigma_{i=1}^{5}$ $w_i \times D_i$ ($\Sigma w_i = 1.0$; $D_i \in [0, 1]$), where values of 0 represent the lowest level of water security and values of 1 the highest, follows the generalized structure adopted by composite indices in the water security literature [8,70]. However, its principal innovation lies not in the equation itself but in determining the weighting coefficients through the Analytic Hierarchy Process (AHP), supported by a multidisciplinary expert panel that explicitly includes representatives of

mining-affected communities. This participatory weighting strategy directly addresses the concerns raised by Hofste et al. (2019) [7] regarding the use of arbitrary weighting schemes in water-risk indices lacking transparent and participatory validation procedures.

Operationalization pathway. The complete calibration of the ICSHM is reserved for the proposed validation phase, but the operational decisions that frame it can be stated now. Individual indicators within each dimension will be normalized to the [0, 1] interval by min–max rescaling, with the orientation of each indicator adjusted so that higher values consistently denote higher water security; indicators where a higher raw value denotes degradation, such as heavy metal concentrations or the proportion of mining area within a buffer zone, will be inverted before aggregation. Missing values in continuous variables will be estimated by spatial interpolation and flagged as a source of uncertainty. Where a dimension cannot be computed for a given spatial unit because too few of its indicators are available, that unit will be reported as incomplete for that dimension rather than imputed. Dimension scores will be obtained as the weighted arithmetic mean of their component indicators, and the dimension weights (w_i) will be derived through the AHP procedure described above. Because a weighted sum permits compensation between dimensions, a sensitivity analysis will test the robustness of the resulting rankings against alternative aggregation rules, including partially non-compensatory schemes, following the procedures recommended for composite indicators [71,72]. Inputs of differing spatial resolution will be resampled to a common 30 m grid, using bilinear interpolation for continuous variables and nearest-neighbour assignment for categorical ones.

Table 9. Proposed conceptual framework of the ICSHM: dimensions, geospatial architecture, key variables, and supporting evidence from the reviewed literature.

Dim.	Dimension	Geospatial Architecture	Key Variables	Evidence from the Reviewed Corpus
D1	Water Availability	G4 (SWAT+, HEC-HMS)	Mean annual streamflow, hydrological variability (IHA), groundwater recharge, water abstraction ratio	Thirteen studies employed G4, but none integrated it with G8 within a composite index.
D2	Water Quality	G1 + G2 (GIS + Optical Remote Sensing)	WQI, turbidity, TSS, Hg/Fe/Mn/As/Pb concentrations, pH, dissolved oxygen	Most frequently adopted methodological combination (G1: 64%; G2: 44%); eight studies combined both methods without developing a composite index
D3	Mining Contamination Risk	G3 + G4 + G5 (SAR/InSAR + distributed hydrological modelling + hydraulic and contaminant transport modelling)	Mining operation density, proximity to the drainage network, AMD probability, tailings storage volume	G3 was underutilized (8%) despite its critical importance for tropical regions with persistent cloud cover.
D4	Ecosystem Integrity	G2 + G6 (Remote Sensing + Landscape Ecology)	Riparian NDVI, LULC change, habitat connectivity, ecological flow ($Q_{7,10}$)	G6 was used in only 8% of studies despite its recognized importance for riparian ecosystem assessment
D5	Sociocultural Vulnerability	G1 + G8 (GIS + Spatial MCDA)	Exposed population, ethnic territories, water supply coverage, food security, environmental conflicts	G8 appeared in only 12% of studies and was never integrated with other categories for comprehensive water security assessment

Note: The proposed ICSHM is defined as $ICSHM = \Sigma_{i=1}^{5} (w_i \times D_i)$, where $\Sigma w_i = 1.0$ and $D_i \in [0, 1]$. Values of **0** represent the lowest level of water security, whereas values of **1** indicate the highest level of water security. The weighting coefficients (w_i) are determined using the Analytic Hierarchy Process based on a multidisciplinary expert panel. The recommended spatial assessment unit is the 1:50,000 watershed scale. Although D2 and D4 both incorporate G2 (optical remote sensing), they address analytically distinct objectives: D2 evaluates the current condition of water quality, whereas D4 assesses the ecological capacity of watersheds to maintain water quality over time [2]. D3 integrates G3 for cloud-penetrating detection, G4 for diffuse contaminant loading and G5 for plume dispersion and tailings dam failure simulation. This three-method integration operationalizes the G4 + G5 + G8 gap reported in Section 3.4: G4 and G5 represent the physical transport of contamination,

while G8 provides the spatial multi-criteria aggregation into the composite index; AMD = Acid Mine Drainage; IHA = Indicators of Hydrologic Alteration; InSAR = Interferometric Synthetic Aperture Radar; LULC = Land Use/Land Cover; MCDA = Multi-Criteria Decision Analysis; NDVI = Normalized Difference Vegetation Index; $Q_{7,10}$ = seven-day low flow with a ten-year return period; SAR = Synthetic Aperture Radar; TSS = Total Suspended Solids; WQI = Water Quality Index.

4.4. Limitations, Uncertainties, and Future Research Agenda

Six limitations deserve explicit consideration.

The first, and perhaps most substantive, concerns the relatively low inclusion rate of 2.7% of the unique records screened (50 of 1847). Although this proportion is consistent with the emerging and interdisciplinary nature of the research field, comparable inclusion rates have been reported by De León Pérez et al. (2024) [12] in systematic reviews of geospatial environmental assessment, and it also suggests that the reviewed corpus may not equally represent all globally relevant mining contexts. The geographical concentration of studies in Brazil (22%) and China (16%) reflects the greater availability of indexed scientific literature in these countries. In Brazil, this predominance is largely explained by the extensive post-Brumadinho datasets and the country's well-established research infrastructure focused on iron mining impacts [35,44,49]. In China, it is primarily associated with the environmental consequences of large-scale coal mining [28,45,51]. By contrast, Colombia (6%) and Sub-Saharan Africa (including Ghana, South Africa, Cameroon, and Egypt) remain underrepresented despite their well-documented socio-environmental complexity [36,53,73–75]. Overall, this distribution suggests that mining regions with greater data availability tend to dominate the scientific literature, whereas equally important but more data-limited contexts remain comparatively underrepresented.

The second limitation concerns the proposed G1–G8 geospatial taxonomy. Developed inductively and refined through informal consultation with researchers in the field, following the general approach of De León Pérez et al. (2024) [12], the taxonomy demonstrates internal consistency and domain-specific validity for water-security assessment in mining contexts. Nevertheless, its categorical boundaries may require refinement when applied to broader environmental assessment domains, where distinctions between, for example, distributed hydrological modeling (G4) and hydraulic and contaminant transport modeling (G5) may become less clearly defined. This limitation concerns the scope of applicability rather than the internal validity of the taxonomy itself.

The third limitation is operational. The free version of Rayyan imposes restrictions on automatic duplicate detection, requiring complementary deduplication procedures using Zotero 7.0. Although the complete documentation of the screening workflow ensures methodological transparency and reproducibility, the possibility that a very small number of duplicate records (estimated at <2%, based on manual verification rates) remained undetected cannot be entirely excluded. Future studies adopting this protocol should consider using the institutional version of Rayyan or alternative deduplication tools offering more advanced automation.

A fourth limitation concerns the conduct of the review itself. Screening and full-text assessment were performed by a single reviewer, which precludes calculation of inter-rater agreement statistics and leaves open the possibility that selection decisions would have been made differently by a second independent reviewer. All decisions were recorded in Rayyan, so the selection path is traceable and reproducible, but traceability is not the same as independent verification. The targeted check of the literature reported in Section 4.3 carries the same qualification: it was conducted to corroborate the identified gap, followed no formal search protocol, and should be read as corroboration rather than as a second systematic review.

A fifth consideration concerns the temporal structure of the hydrological processes that drive the indicators. Water quality in a mining-affected watershed does not vary randomly around a mean: streamflow, rainfall and the water quality series that depend on them exhibit long-term persistence, a tendency for wet and dry conditions to cluster over multi-annual scales. Dimitriadis et al. (2021) [76] show

that this behaviour is a general property of hydrological-cycle processes at the global scale, and Koirala et al. (2011) [77] document it specifically in hydrologic and water quality time series through Hurst analysis. The practical consequence for the ICSHM is that the same mining operation can yield markedly different observed contamination levels depending on whether the assessment window falls during a wet or dry phase of such a cycle. In its present formulation the index does not account for this: indicators derived from distributed hydrological modelling (G4) and from time-series remote sensing (G7) describe mean or threshold conditions and may therefore understate variability under extreme hyper-annual cycles. Incorporating a persistence metric such as the Hurst parameter as a covariate in D1 and D3 would characterise the temporal stability of the assessed conditions, and is reserved for the validation phase.

The sixth limitation is conceptual and constitutes the principal direction for future research. The proposed Mining Water Security Composite Index ICSHM assumes that the five dimensions identified through this systematic review are sufficient to operationalize water security in mining-affected watersheds. This assumption requires empirical validation before it can be considered fully supported by evidence. It is entirely plausible and methodologically appropriate to anticipate that future validation studies may identify additional dimensions, reveal limitations in the variables currently assigned to each dimension, or demonstrate that the weighting coefficients (w_i) vary systematically across different mining typologies, thereby requiring context-specific parameterization of the unified index. Rather than weakening the contribution of the present study, this possibility reinforces its scientific value by establishing the analytical framework within which these questions can be rigorously investigated.

The next stage of this research will focus on implementing, calibrating, and validating the ICSHM in mining-affected watersheds representing contrasting mining typologies, thereby testing both its conceptual architecture and its operational applicability under real-world environmental conditions.

5. Conclusions

This systematic review identified a double gap in the literature on geospatial water security assessment in mining-affected watersheds. First, none of the 17 indices identified in the reviewed corpus simultaneously integrates the five dimensions proposed in this review for the comprehensive assessment of water security in extractive contexts. Second, the methodological combination of distributed hydrological modeling (G4), hydraulic and contaminant transport modeling (G5), and spatial multi-criteria decision analysis (G8) was absent from all 50 studies conducted across 22 countries over the past two decades. These findings demonstrate that the observed fragmentation is not incidental but structural, reflecting the independent evolution of disciplinary approaches in the absence of an integrative conceptual framework.

The proposed G1–G8 geospatial taxonomy, developed inductively from the reviewed corpus, provides a domain-specific classification framework for evaluating the degree of geospatial methodological integration in studies of mining-related water security. Beyond its application to mining, its diagnostic capability, making methodological absences quantitatively explicit, offers potential for transfer to other areas of geospatial environmental assessment where methodological fragmentation similarly constrains scientific progress.

The proposed Mining Water Security Composite Index ICSHM establishes an explicit conceptual architecture linking five dimensions of water security with the geospatial methods that operationalize them and the empirical evidence supporting each design decision. The next stage of this research will involve the empirical implementation, calibration, and validation of the ICSHM in watersheds representing contrasting mining typologies, using a participatory Analytic Hierarchy Process (AHP) with a multidisciplinary expert panel that explicitly includes representatives of mining-affected communities.

Regardless of whether this validation confirms or refines the proposed conceptual architecture, it will provide the first empirical evidence regarding the applicability of an integrated composite index for assessing water security in mining-affected watersheds. Such evidence is a precondition for applying the

index in environmental licensing, watershed management, or land-use planning in mining regions. Until the proposed validation study is completed, the contribution of the present work remains the systematic synthesis and the conceptual architecture it supports.

More broadly, this study provides a methodological foundation for the next generation of geospatial water security assessments in mining-affected watersheds, where hydrological processes, environmental contamination, ecosystem integrity, and sociocultural vulnerability are evaluated within a unified analytical framework.

Statement of the Use of Generative Artificial Intelligence (AI) and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) and Claude (Anthropic) to assist with language editing, manuscript drafting, structural organization, and improvement of the clarity and readability of the text. The AI tools were used exclusively to support the writing process and did not contribute to the generation, analysis, interpretation, or validation of the scientific results. After using these tools, the authors carefully reviewed, revised, and edited all content and took full responsibility for the accuracy, originality, and integrity of the published work.

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Author Contributions

Conceptualization, J.S.C., M.A.N. and H.E.M.A.; Methodology, J.S.C.; Validation, J.S.C.; Formal Analysis, J.S.C.; Investigation, J.S.C.; Data Curation, J.S.C.; Writing—Original Draft Preparation, J.S.C.; Writing—Review & Editing, J.S.C., M.A.N., H.E.M.A., K.V.d.A., J.A.L., V.B.N.C., L.d.C.M., A.M.d.C. and B.M.F.; Visualization, J.S.C.; Supervision, M.A.N.; Project Administration, J.S.C. All authors have read and agreed to the published version of the manuscript.

Ethics Statement

This study is based exclusively on the analysis of previously published scientific literature and did not involve human participants, animals, clinical data, or primary data collection. Consequently, ethical approval and informed consent were not required. The systematic review was conducted in accordance with the PRISMA 2020 guidelines and adhered to internationally accepted principles of research integrity, transparency, and responsible scientific reporting.

Informed Consent Statement

Not applicable. This study is a systematic review based exclusively on previously published literature and did not involve human participants or the collection of primary data.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. These data include the systematic review protocol, study selection records, data

extraction tables, methodological quality assessment, and the geospatial taxonomy developed during the review process.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the research, authorship, and/or publication of this article.

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