earth

MDPI

Systematic Review

A Systematic Review of River Discharge Measurement Methods: Evolution and Modern Applications in Water Management and Environmental Protection

Oscar Abel González-Vergara [1], María Teresa Alarcón-Herrera [1], Ana Elizabeth Marín-Celestino [2], Armando Daniel Blanco-Jáquez [1], Joel García-Pazos [1], Samuel Villarreal-Rodríguez [1], Yolocuauhtli Salazar [3] and Diego Armando Martínez-Cruz [4,*]

[1] Centro de Investigación en Materiales Avanzados, S.C. Calle CIMAV 110, Ejido Arroyo Seco, Col. 15 de mayo, Durango 34147, Mexico; oscar.gonzalez@cimav.edu.mx (O.A.G.-V.); teresa.alarcon@cimav.edu.mx (M.T.A.-H.); armando.blanco@cimav.edu.mx (A.D.B.-J.); joel.garcia@cimav.edu.mx (J.G.-P.); samuel.villarreal@cimav.edu.mx (S.V.-R.)

[2] SECIHTI—Instituto Potosino de Investigación Científica y Tecnológica, A.C. División de Geociencias Aplicadas, Camino a la Presa San José 2055, Col. Lomas 4ta Sección, San Luis Potosí 78216, Mexico; ana.marin@ipicyt.edu.mx

[3] Postgraduate Program in Engineering, Tecnológico Nacional de México/IT Durango, Blvd. Felipe Pescador 1830 Ote., Durango 34080, Mexico; ysalazar@itdurango.edu.mx

[4] SECIHTI—Centro de Investigación en Materiales Avanzados, S.C. Calle CIMAV 110, Ejido Arroyo Seco, Col. 15 de mayo, Durango 34147, Mexico

* Correspondence: diego.martinez@cimav.edu.mx; Tel.: +52-614-439-4898

Abstract

Accurate river discharge estimation is fundamental for water resource management under increasingly variable hydrological conditions. While conventional in situ techniques remain hydrometric reference standards, their operational deployment is constrained by cost, accessibility, and limited spatial coverage. Advances in remote sensing and artificial intelligence (AI) have introduced non-contact discharge estimation frameworks based on image-derived observations. This systematic review, conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting guidelines, examines the evolution of river discharge measurement methods between 2004 and 2024 through a structured two-stage design. An initial search in Web of Science and Scopus identified 2809 records, of which 249 were retained for first-stage synthesis. A focused second-stage screening isolated seven studies that directly integrate image-based data with machine learning or deep learning architectures for discharge estimation. The analysis reveals a methodological transition from instrument-based hydrometry toward computationally assisted, image-driven approaches. The retained studies employ close-range and satellite imagery combined with Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and related models. Although reported validation metrics indicate strong predictive capability under specific conditions, performance remains dependent on site-specific calibration and reference discharge records. Broader operational deployment requires improved transferability, uncertainty integration, and cross-basin validation.

Keywords: artificial intelligence; deep learning; remote sensing; river discharge estimation; hydrological monitoring; non-intrusive measurement

Check for updates

Academic Editors: Leszek Sobkowiak and David Post

Received: 13 January 2026
Revised: 20 February 2026
Accepted: 2 March 2026
Published: 6 March 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Effective water resource management depends on reliable monitoring and estimation of river discharge, particularly under increasingly frequent hydrological extremes such as floods and droughts associated with climate variability and change [1,2]. Conventional in situ approaches, including current meters, rating curves, and Doppler-based instrumentation, remain widely used reference techniques because they are supported by established hydrometric protocols [3,4]. However, their operational deployment often requires site accessibility, physical installation, and sustained maintenance, which can limit spatial coverage and reduce feasibility in remote, hazardous, or resource-constrained settings [5–8].

In parallel, advances in remote sensing and computational methods have expanded the range of non-contact observations available for hydrological inference. Satellite and close-range imagery can provide spatially distributed surface information relevant to discharge estimation, while machine learning and deep learning techniques offer flexible modeling frameworks for modeling nonlinear relationships in complex hydrological systems [9,10]. Recent work has explored image-based learning pipelines in which Convolutional Neural Networks capture spatial patterns from imagery, and sequence models such as Long Short-Term Memory networks represent temporal dynamics when time-resolved observations are available [11–14].

Despite rapid growth in this area, the literature remains methodologically heterogeneous. Many studies apply AI to hydrometeorological time series without imagery [11,15–18], while others use remote sensing products for hydrological variables that are not direct discharge targets [19–21]. In addition, image-based approaches often depend on site-specific calibration and validation against reference discharge records, which complicates cross-study comparability and limits immediate operational transferability. Recent developments also include distributed IoT-based hydrometric monitoring systems integrating anomaly detection and wireless communication technologies [22,23]. A consolidated synthesis that connects the broader historical evolution of discharge measurement with a focused assessment of image-based AI frameworks is therefore needed.

This systematic review addresses that need through a two-stage design. The first stage maps the evolution of river discharge estimation methods between 2004 and 2024 using structured screening and bibliometric analysis to characterize thematic and temporal transitions. The second stage applies conceptually focused inclusion criteria to isolate studies that directly estimate river discharge using image-derived observations integrated with AI or machine learning, enabling a targeted technical synthesis of contemporary image-based frameworks and their operational constraints.

Accordingly, the review is guided by the following research question:

How have river discharge estimation methods evolved between 2004 and 2024, and to what extent can image-based artificial intelligence frameworks help mitigate key limitations of conventional approaches under current and emerging water management challenges?

To answer this question, the objectives are:

To systematically synthesize the evolution of river discharge estimation approaches and conduct a bibliometric analysis of temporal, geographic, and keyword trends that characterize the methodological transition from conventional hydrometry toward non-intrusive and computationally assisted strategies.

To perform a focused technical synthesis of image-based AI studies that directly estimate river discharge, describing sensing configurations, model architectures, validation dependencies, and operational constraints to inform research priorities and practical deployment.

2. Materials and Methods

This systematic review was conducted in accordance with PRISMA 2020 guidelines [24]. The review protocol was not registered. A two-stage design was adopted to map the broader evolution of river discharge estimation methods between 2004 and 2024 and isolate and technically synthesize studies that directly integrate image-derived observations with artificial intelligence or machine learning for river discharge estimation.

Figure 1 presents the PRISMA flow diagram. Records were identified through database searches, exported to a reference manager for deduplication, and screened using predefined eligibility criteria. Stage 1 retained studies addressing river discharge estimation across conventional and computational approaches, whereas Stage 2 applied focused inclusion criteria to identify image-based AI/ML frameworks in which imagery constitutes a primary quantitative input and discharge is the modeled target variable.

2.1. Search Strategy

A systematic search was conducted in Web of Science (WoS) and Scopus to capture peer-reviewed literature on river discharge estimation and related flow measurement methods. These databases were selected due to their broad coverage of hydrology, remote sensing, and computational modeling research. The search strategy combined three conceptual groups: (i) flow and discharge measurement terminology, (ii) conventional hydrometric instrumentation and monitoring approaches, and (iii) artificial intelligence/machine learning and remote sensing terms relevant to image-derived hydrological inference. The complete search strings applied in each database are provided in Table 1.

The search strategy was intentionally broad to maximize recall of river discharge studies that may be indexed under generic flow measurement terminology; thematic specificity was subsequently enforced during screening through predefined river-focused eligibility criteria.

Eligibility was restricted to English-language journal articles published between 2004 and 2024 and was executed on 24 October 2024. The language restriction was applied to ensure consistency in screening and data extraction, and because most of the internationally indexed, peer-reviewed literature in this field is published in English in WoS and Scopus. The selected temporal window captures two decades of methodological development, including the emergence of image-based and AI-assisted discharge estimation.

Table 1. Search string for Scopus and Web of Science.

Database	Search String
Scopus	TITLE-ABS-KEY ((“Mechanical Water Meter” OR “Reed-Type Water Meter” OR “Photoelectric Read-Only Water Meter” OR “Weir method” OR “slot method” OR “volume method” OR “bouy method” OR “Electromagnetic flow meter” OR “ultrasonic flow meter” OR “turbine flow meter” OR “vortex flow meters” OR “velocimetry” OR “Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Neural Networks” OR “ANN” OR “Remote Sensing” OR “IoT” OR “Internet of Things” OR “Big Data” OR “CNN” OR “smart sensors” OR “real-time monitoring” OR “sensor networks” OR “Traditional methods” OR “Traditional Measurement Methods” OR “manual methods” OR “hydrometric methods” OR “empirical methods”) AND (“water flow measurement” OR “water flow monitoring methods” OR “river water flow” OR “water flow monitoring” OR “water flow monitoring systems” OR “river discharge” OR “water level monitoring” OR “water flow testing technologies” OR “canal water flow” OR “canal discharge” OR “water flow in canals” OR “canal flow measurement” OR “Water measurement instruments” OR “water flow rate”)) AND DOCTYPE (ar) AND PUBYEAR > 2003 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE, “English”))

Table 1. *Cont.*

Database	Search String
Web of Science	TS = ((“Mechanical Water Meter” OR “Reed-Type Water Meter” OR “Photoelectric Read-Only Water Meter” OR “Weir method” OR “slot method” OR “volume method” OR “bouy method” OR “Electromagnetic flow meter” OR “ultrasonic flow meter” OR “turbine flow meter” OR “vortex flow meters” OR “velocimetry” OR “Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Neural Networks” OR “ANN” OR “Remote Sensing” OR “IoT” OR “Internet of Things” OR “Big Data” OR “CNN” OR “smart sensors” OR “real-time monitoring” OR “sensor networks” OR “Traditional methods” OR “Traditional Measurement Methods” OR “manual methods” OR “hydrometric methods” OR “empirical methods”)) AND TS = (“water flow measurement” OR “water flow monitoring methods” OR “river water flow” OR “water flow monitoring” OR “water flow monitoring systems” OR “river discharge” OR “water level monitoring” OR “water flow testing technologies” OR “canal water flow” OR “canal discharge” OR “water flow in canals” OR “canal flow measurement” OR “Water measurement instruments” OR “water flow rate”) AND DT = (Article) AND PY = (2004–2024) AND LA = (English)

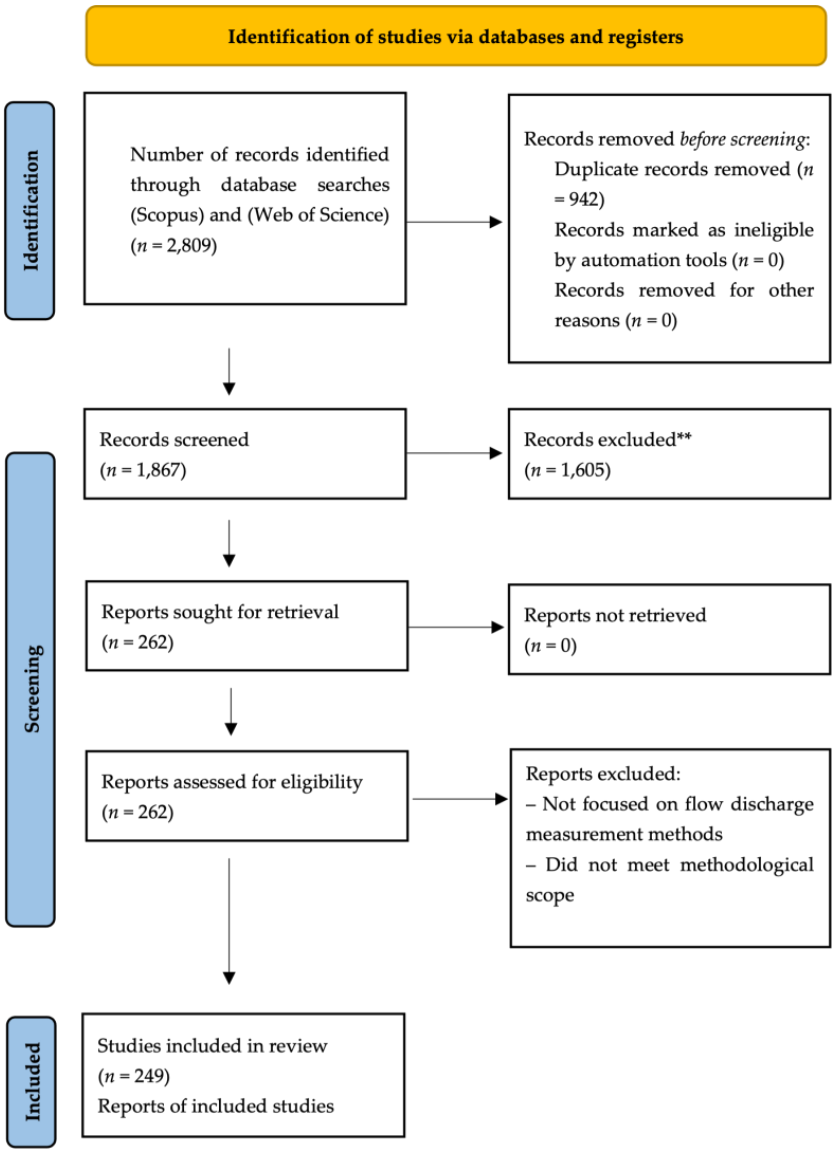

Figure 1. PRISMA 2020 flow diagram for study identification, screening, eligibility, and inclusion adapted from Page et al. [24]. ** Records excluded during title and abstract screening based on predefined eligibility criteria described in Section 2.2.

All records were exported to Zotero (v7.0.24) for reference management. Duplicate entries across databases were removed using Zotero's duplicate detection tool followed by manual verification. After deduplication, 1867 unique records were retained for title and abstract screening.

2.2. Selection Criteria and Study Screening

Reference management and screening were conducted using a structured, multi-step workflow designed to enhance transparency and reproducibility. After duplicate removal in Zotero (see Section 2.1), records were exported to ASReview to support relevance-based prioritization during title and abstract screening. ASReview was configured using Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction and a Naive Bayes classifier to iteratively rank records according to predicted relevance. Human reviewers retained full control over inclusion decisions throughout the process. Additional methodological details regarding the ASReview configuration and screening workflow are provided in the Supplementary Materials.

To ensure the inclusion of relevant and high-impact journal vs article without high impact factors were excluded, and a two-stage screening process was established.

2.2.1. First-Stage Screening

The first-stage screening aimed to capture the broad methodological landscape of river discharge estimation. Titles and abstracts were evaluated against predefined eligibility criteria:

1. Peer-reviewed journal articles indexed in Web of Science or Scopus.
2. Empirical or experimentally validated studies.
3. Explicit focus on river discharge measurement or estimation methods, including conventional hydrometric and computational approaches.

Studies focusing exclusively on water distribution systems, sewer networks, irrigation canals without river context, or purely theoretical modeling without empirical validation were excluded.

Journal quartile classification (Q1–Q2) was considered during the initial screening stage as an auxiliary indicator of editorial and methodological standards. However, inclusion decisions were ultimately based on methodological relevance and empirical validation rather than journal ranking alone. Quartile classification was not applied as a filtering criterion during the second-stage conceptual selection. All retained studies were indexed in internationally recognized databases and subject to peer review.

2.2.2. Second-Stage Screening

The second-stage screening applied conceptually focused inclusion criteria to isolate image-based artificial intelligence frameworks for river discharge estimation. To ensure internal methodological coherence, studies were required to simultaneously satisfy all of the following conditions:

1. Use of image-derived or spatially explicit remote sensing inputs (e.g., close-range optical imagery, UAV imagery, satellite optical or SAR data).
2. Implementation of machine learning or deep learning architectures (e.g., CNN, LSTM, ANN, SVR, transformer-based models).
3. Direct estimation of river discharge as the primary target variable (Q), rather than intermediate hydrological variables (e.g., water level, velocity-only outputs, or flood extent).
4. Empirical validation against reference discharge measurements (e.g., gauge stations, ADCP, or equivalent hydrometric benchmarks).

Studies that employed machine learning exclusively on hydrometeorological time series without image input, or that applied image-based methods without AI/ML integration, were excluded at this stage.

This structured two-stage screening process resulted in the identification of seven studies for final synthesis in Stage 2. The reduction reflects the application of conceptually strict methodological criteria rather than a scarcity of AI-related hydrological research.

2.3. Analysis and Synthesis of Information

Following study selection, a structured data extraction framework was applied to enable systematic comparison across the retained corpus. The framework was designed to support analytical synthesis rather than quantitative aggregation and to ensure consistency in how methodological and operational attributes were documented.

Instead of reapplying eligibility criteria, this stage focused on characterizing how discharge estimation approaches were implemented in practice. Extracted variables captured: modeling configuration (including algorithmic architecture and discharge inference strategy), characteristics of the input data (including sensing modality, spatial scale, and temporal resolution), validation configuration and reported evaluation metrics, and operational considerations affecting scalability and transferability.

Performance indicators (e.g., NSE, RMSE, R^2, KGE) were recorded exactly as reported in the original publications. No metric normalization or cross-study statistical comparison was conducted due to heterogeneity in hydrological regimes, validation schemes, and evaluation definitions. Accordingly, performance results were interpreted contextually rather than comparatively.

Operational aspects were examined qualitatively, including dependency on reference discharge data for calibration, sensitivity to environmental conditions, computational requirements, and reported constraints on transferability across hydrological regimes and sites. This approach allowed identification of structural patterns and methodological convergence without imposing artificial equivalence across heterogeneous study designs.

The extracted variables are summarized in Table 2. Synthesis was conducted through comparative analytical interpretation, forming the basis for technical profiling (Section 3.5) and the critical assessment of limitations (Section 3.6).

Table 2. Data extraction framework applied to the selected studies.

Category	Extracted Variables	Description/Criteria
Methodological characteristics	Type of approach	Classification of the method as traditional, machine learning, deep learning, or hybrid
	Model/algorithm	Specific architecture or algorithm used (e.g., CNN, LSTM, CNN–LSTM, transformer-based models)
	Modeling strategy	Direct discharge estimation, velocity-to-discharge conversion, hybrid or physics-informed approach
Data characteristics	Data source	Type of input data (e.g., close-range imagery, UAV video, satellite imagery, in situ measurements)
	Spatial scale	Reach-scale, watershed-scale, or regional-scale application
	Temporal resolution	Event-based, daily, or continuous monitoring
	Data volume and labeling	Reported size of training datasets and dependence on labeled data
Validation configuration and reported indicators	Performance metrics	Metrics reported by authors (e.g., NSE, RMSE, R^2, KGE)
	Validation strategy	Cross-validation, independent test sites, or comparison with conventional methods
Operational applicability and limitations	Computational demand	Qualitative assessment of computational cost (low, medium, high)

Table 2. *Cont.*

Category	Extracted Variables	Description/Criteria
	Model interpretability	Degree to which model outputs and internal behavior can be explained
	Transferability	Applicability to ungauged, data-scarce, or remote regions
	Operational feasibility	Potential for real-time monitoring or integration into water management systems
	Reported limitations	Key limitations identified by the authors

2.4. Visualization of Results and Methodological Mapping

Based on the structured variables extracted through the data framework (Section 2.3), bibliometric and thematic analyses were performed to support interpretation of the broader methodological evolution identified in Stage 1. Visualization techniques were used as complementary analytical tools to identify temporal patterns, thematic clustering, and conceptual linkages within the screened corpus.

Keyword co-occurrence and citation density analyses were conducted using VOSviewer (version 1.6.20). Network maps and temporal overlay visualizations were generated to examine relationships among dominant terms and to assess the relative prominence of traditional hydrometric instrumentation and emerging image-based and AI-driven approaches over time.

Geographic distribution and publication trends were analyzed descriptively to contextualize research concentration patterns across countries and institutions. Because bibliometric patterns can be influenced by database coverage and indexing practices, these analyses were interpreted as indicative rather than exhaustive representations of global research activity.

The integration of structured data extraction (Section 2.3) with bibliometric visualization supports a coherent methodological link between screening, synthesis, and results interpretation. All visualization outputs are directly traceable to the extracted variables and database-derived metadata, ensuring transparency and reproducibility.

3. Results and Discussion

3.1. Historical and Thematic Evolution of River Discharge Estimation Methods: First Substage

Following the first-stage screening (n = 249), the resulting corpus provides a comprehensive representation of methodological developments in river discharge estimation between 2004 and 2024. This stage captures the broader evolution of surface water monitoring technologies prior to the focused synthesis of image-based artificial intelligence approaches presented in Section 3.2.

During the early portion of the study period, research was predominantly centered on intrusive or semi-intrusive techniques, including current meters, Doppler-based instrumentation, rating curves, and conventional stream gaging stations. These methods remain established reference standards due to their high reliability and accuracy under controlled hydrometric conditions. However, their implementation requires physical installation, regular maintenance, and site accessibility, which constrain scalability, limit applicability in remote or hazardous environments, and restrict monitoring in ungauged basins.

From approximately the mid-2010s onward, a consistent increase in non-intrusive and spatially distributed monitoring approaches becomes observable. This transition coincides with improvements in satellite sensor resolution, expanded access to long-term Earth observation archives, and increased computational capacity for large-scale data processing. Remote sensing technologies progressively evolved from complementary observational

tools to primary data sources for hydrological inference, enabling discharge-related analysis across broader spatial and temporal domains.

Keyword co-occurrence and citation density analyses (Figure 2) reveal that "remote sensing" occupies a central position within the thematic network, indicating strong conceptual linkages with velocity measurement techniques, Doppler-based instrumentation, and emerging computational methods. Temporal overlay visualization (Figure 3) further illustrates the chronological progression of research themes. Earlier publications are strongly associated with terms such as "stream gaging," "Doppler," and "velocity measurement," reflecting instrument-based hydrometry. In contrast, more recent studies increasingly emphasize "remote sensing," "machine learning," and "neural networks," indicating a gradual integration of data-driven modeling within hydrological research. The temporal distribution of AI-related terminology suggests a sustained methodological reorientation after 2018 rather than a transient research trend.

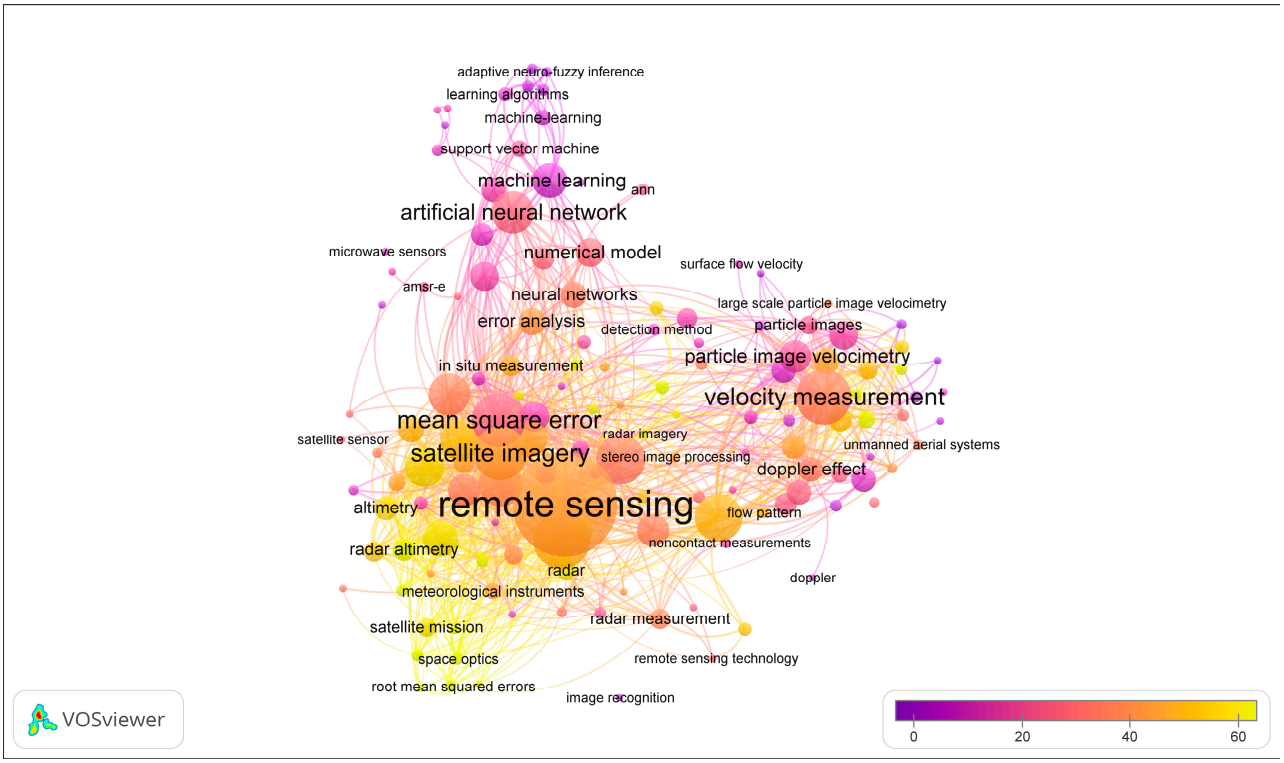

Figure 2. Analysis of keyword occurrences and citations (VOSViewer).

Figure 4 provides a focused evaluation of the relationships among dominant keywords, highlighting the conceptual proximity between "remote sensing," "flow velocity," "velocity measurement," and "Doppler effect." These associations confirm that advances in discharge estimation are closely tied to developments in surface velocity monitoring and remote sensing integration. Additionally, the individual keyword occurrence analysis presented in Figure 5 quantitatively reinforces the centrality of remote sensing-related terminology within the first-stage corpus.

Importantly, this evolution appears to be driven not only by algorithmic innovation but also by operational demands. Growing requirements for continuous monitoring, rapid assessment during extreme hydrological events, and discharge estimation in data-scarce regions have accelerated interest in non-contact and scalable measurement strategies. These contextual pressures help explain the emergence of image-based and AI-enabled frameworks analyzed in the second substage, while distinguishing them from broader machine learning applications based solely on hydrometeorological time series.

For temporal clarity and to enhance interpretability, keyword frequency aggregation in Table 3 focuses on the period 2009–2024. While the corpus includes publications dating back to 2004 (as reflected in the continuous temporal overlay shown in Figure 3), frequency patterns became more interpretable from 2009 onward due to increased thematic density in the screened corpus.

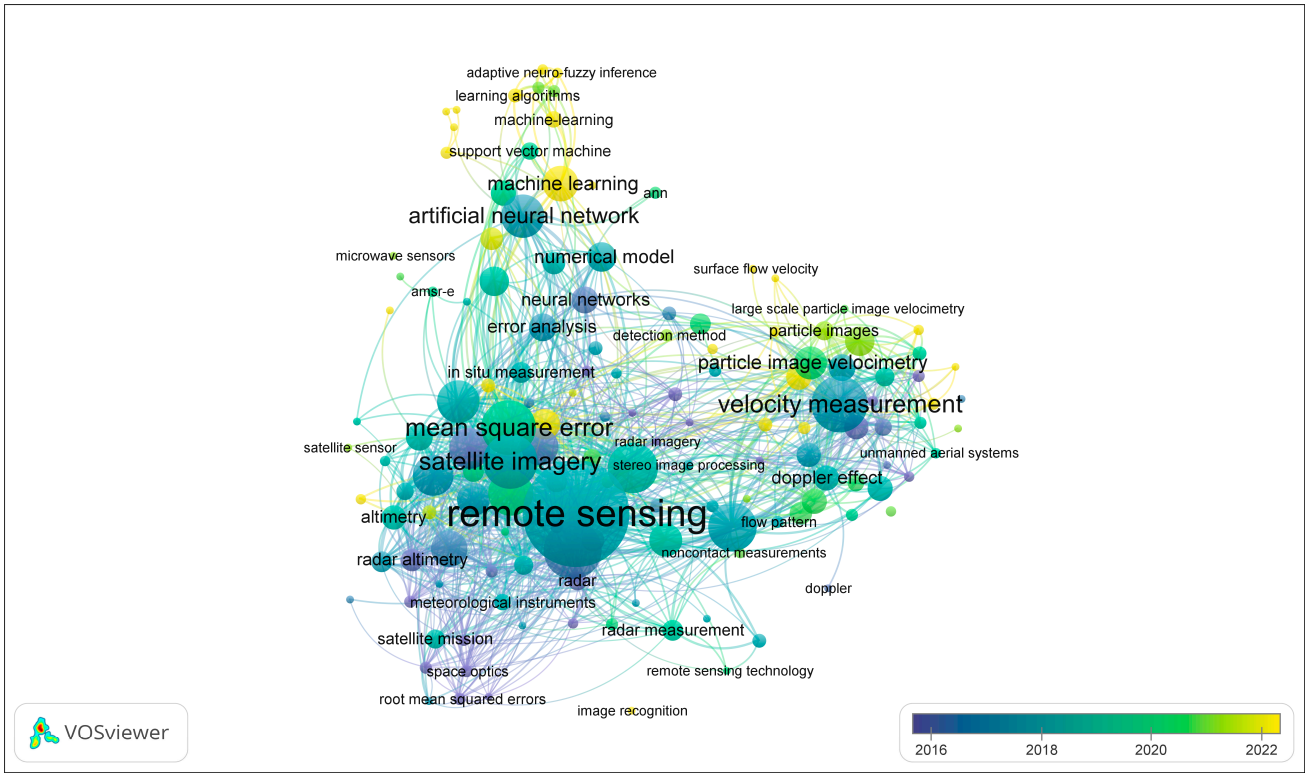

Figure 3. Analysis of occurrences versus average publication year (VOSViewer).

Table 3. Keyword analysis of the first screening stage with the year of occurrence.

Measurement Approach	Representative Keywords	Occurrences 2013–2016	Occurrences 2017–2020	Occurrences 2021–2024
Intrusive surface water methods	Stream gaging, Current meter, Acoustic Doppler Current Profiler (ADCP), Doppler velocity, In situ instrumentation	14	69	14
Non-intrusive surface water methods (remote sensing-based)	Remote sensing, Satellite imagery, Radar altimetry, SAR, UAV, Optical imagery	48	172	94
Non-intrusive surface water methods (computational/AI-enhanced)	Machine learning, Artificial neural network, CNN, LSTM, Deep learning	32	118	92
Image-based velocimetry techniques	Particle Image Velocimetry (PIV), Large-Scale PIV (LSPIV), STIV, Optical flow	52	185	62

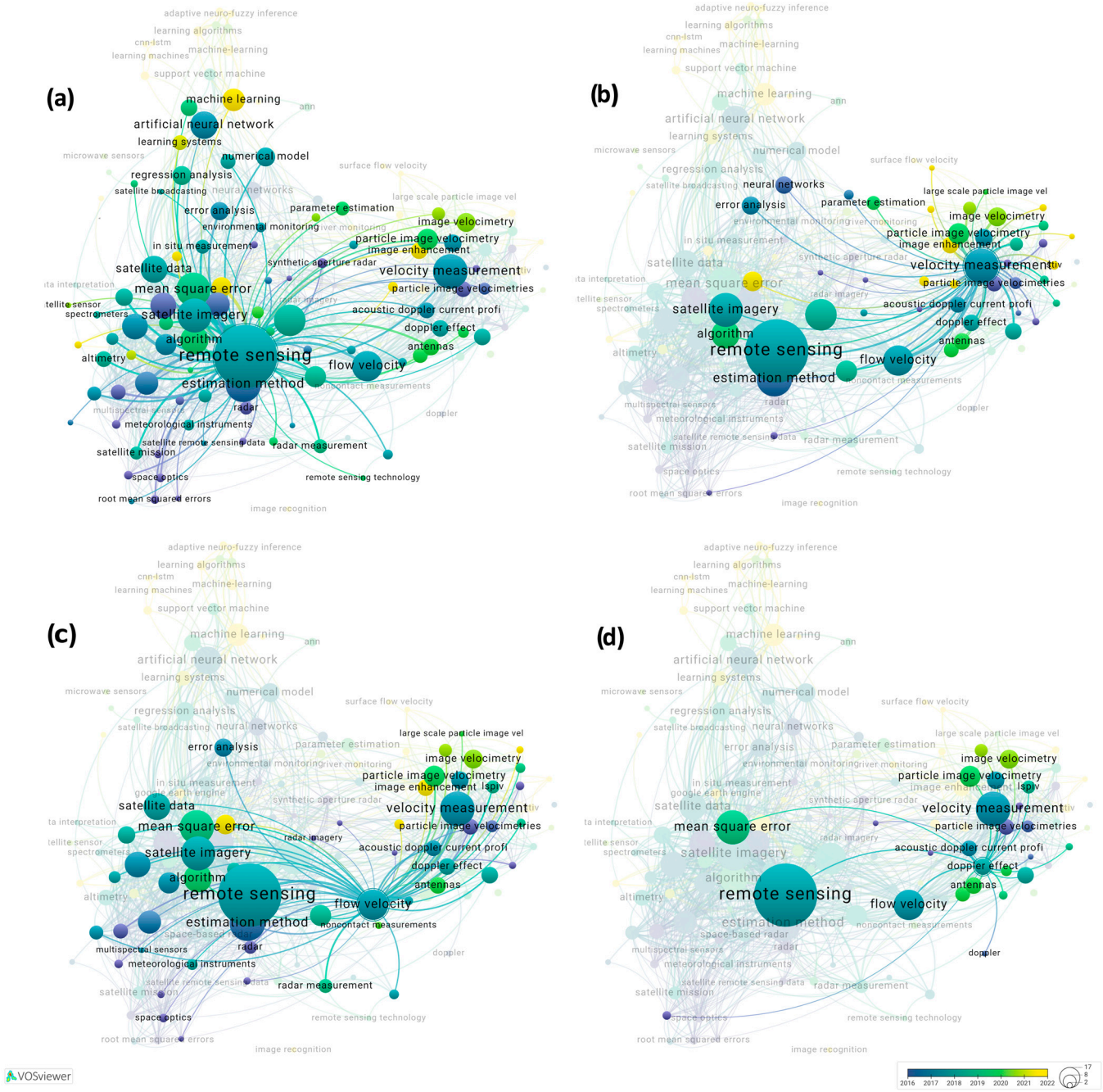

Figure 4. Keyword evaluation (VOSViewer): (**a**) remote sensing analysis, (**b**) velocity measurement analysis, (**c**) flow velocity analysis, and (**d**) Doppler effect analysis.

Table 3 presents keyword frequency trends within the first-stage corpus, focusing exclusively on surface water discharge measurement techniques. The classification distinguishes between intrusive instrumentation-based approaches and non-intrusive methods, including both remote sensing-driven monitoring and computationally enhanced frameworks. The observed increase in non-intrusive and AI-related terms during the 2017–2024 period supports the transition described above, while the continued presence of in situ instrumentation reflects the persistence of conventional gauging systems within the evolving methodological landscape.

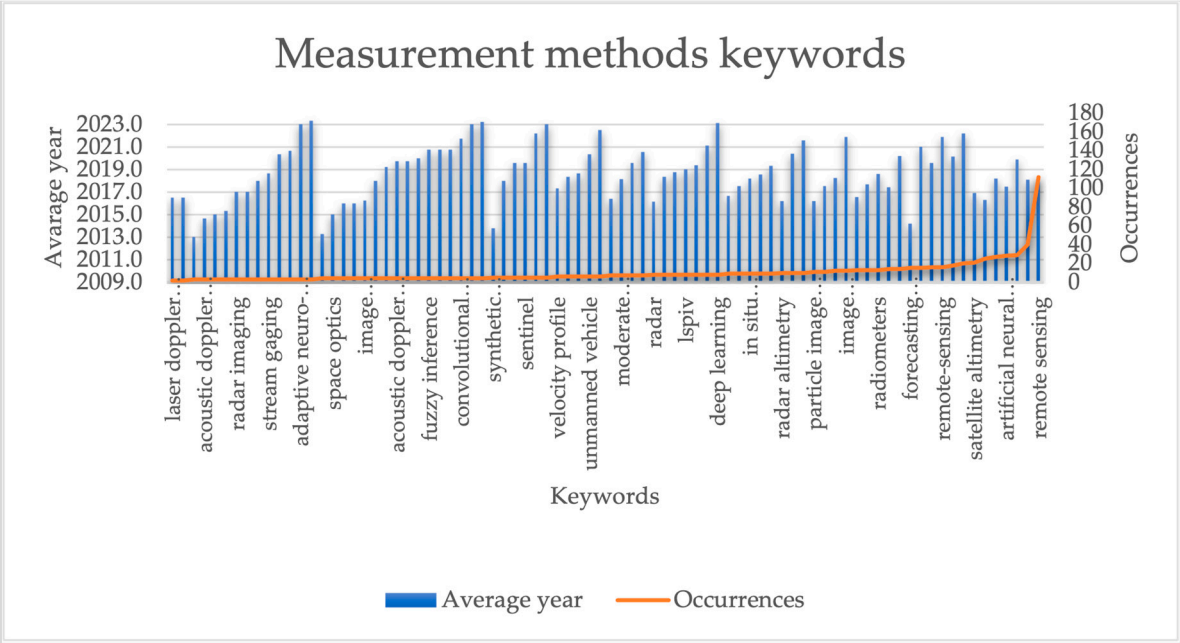

Figure 5. Individual keyword analysis of the first screening stage by occurrences.

Geographically, the United States (n = 73) and China (n = 49) account for the highest number of publications within the first-stage corpus, followed by Italy (n = 32) and France (n = 29). Additional contributions originate from the United Kingdom (n = 19), India (n = 15), Japan (n = 15), Canada (n = 13), Iran (n = 13), and Germany (n = 11), corresponding to the top 10 countries by document count. Because documents may include co-authors from multiple countries, country-level publication counts are not mutually exclusive and therefore exceed the total number of screened articles.

Overall, the first-stage synthesis reveals a clear conceptual progression: from localized, instrument-dependent discharge measurement toward spatially distributed, computationally assisted, and increasingly automated hydrological inference. Nevertheless, this transition does not imply the obsolescence of conventional gauging systems. Instead, it reflects an ongoing hybridization process in which traditional instrumentation remains fundamental for validation and calibration—a dependency on reference discharge measurements that remains central to contemporary frameworks.

3.2. Second Substage: Image-Based Artificial Intelligence Approaches in River Discharge Estimation

The second substage focuses on studies that explicitly integrate image-derived observations with artificial intelligence or machine learning techniques for river discharge estimation. In contrast to the broader first-stage corpus, this substage isolates frameworks in which imagery constitutes a primary quantitative input and AI/ML models are directly involved in discharge inference.

Across the retained studies, inputs originate from two principal sensing contexts: close-range optical imagery and satellite-based observations. Close-range approaches employ RGB water-surface imagery and apply deep learning architectures—including Convolutional Neural Networks and transformer-based models—to relate visual surface characteristics to discharge estimates. Satellite-based approaches leverage medium-resolution optical imagery and, in some cases, multi-source combinations that may include SAR products, radar altimetry, or satellite-derived thermal indicators. In these configurations, machine learning models such as CNN-based architectures, support vector regression, and

artificial neural networks are used to model nonlinear relationships between image-derived predictors and discharge.

Despite differences in sensing platforms and model families, implementations commonly follow a consistent workflow: extraction of quantitative descriptors from imagery and associated observation products, AI/ML-based modeling of the discharge–predictor relationship, and calibration against reference discharge records. Within this structure, imagery functions as a measurable hydrological input embedded in data-driven inference pipelines rather than as a purely qualitative observational layer.

Geographically, the retained studies are predominantly associated with China (n = 4), followed by single contributions from the United States, Canada, and Iran. This distribution indicates that current image-based AI discharge research remains concentrated within specific research groups rather than representing a globally distributed operational framework.

Overall, the second substage delineates the principal configurations through which image-based AI/ML has been applied to river discharge estimation within the reviewed corpus.

3.3. Comparative Analysis of Conventional and AI-Based Methods for River Discharge Estimation

In accordance with the objectives of this systematic review, Table 4 provides a structured comparison between conventional discharge measurement techniques and imagery-based AI approaches retained in Stage 2. The comparison emphasizes differences in data acquisition strategies, modeling structures, operational constraints, and scalability characteristics rather than direct numerical performance ranking.

Performance indicators differ across studies (e.g., NSE, R^2, MRE) and are reported as presented in the original publications. Because these metrics are derived under different hydrological contexts and validation protocols, direct numerical comparison across methodological categories is not strictly equivalent and should be approached with methodological caution.

Conventional methods—including float measurements, current meters, rating curves, and acoustic Doppler current profilers (ADCP)—are based on direct field observations or in-stream instrumentation. These techniques are widely regarded as hydrometric reference standards due to their established measurement protocols and controlled calibration procedures. However, their deployment requires physical access to the river channel, regular maintenance, and site-specific infrastructure, which can limit applicability in remote, hazardous, or ungauged environments.

In contrast, image-based AI-driven discharge estimation approaches rely on non-contact data acquisition through close-range optical systems or satellite observations. Rather than directly measuring velocity or cross-sectional profiles within the channel, these frameworks infer discharge from remotely sensed surface indicators using data-driven modeling architectures. This distinction reflects a shift from physically instrumented measurement toward computationally mediated discharge inference supported by spatially distributed observations.

Table 4. Structural comparison of methodological characteristics and reported performance indicators of selected discharge estimation approaches.

Method Category	Representative Example	Data Source	Reported Validation Indicators	Advantages	Limitations	Operational Applicability	Key References
Traditional Manual Methods	Float method, current meter	Direct field observation, surface velocity	Low–Medium accuracy; high uncertainty during extreme flows	Low cost, simple implementation	Subjective, operator-dependent, unsafe in high flows	Small local rivers	[7,8]
Instrumental In Situ Methods	ADCP, electromagnetic sensors	In-stream velocity profiling and bathymetric measurements	High discharge measurement precision; 3D velocity profiling; transect-based discharge computation	High-resolution velocity structure; reliable cross-sectional discharge quantification	Requires field deployment, vessel access, trained operators; cost-intensive	Gauged river sections; accessible monitoring sites	[25]
Close-Range Imaging + Deep Learning	RivQNet (DL velocimetry)	RGB imagery/video (shore-based or UAV)	NSE ≈ 0.89–0.95; RMSE dependent on flow regime	Non-intrusive, reduces subjective processing, suitable for dynamic rivers	Requires labeled training data and stable image acquisition	Site-specific monitoring, flood-prone rivers	[5]
Webcam-Based Deep Learning Gaging	Imaging-based stream gaging	Fixed optical cameras + stage reference	Comparable performance to traditional gauging in tested sites	Continuous remote monitoring, low field risk	Sensitive to lighting, site calibration needed	Gauged rivers with camera installation	[13]
Satellite Optical Imagery + ML/DL	Landsat-based discharge estimation	Multispectral satellite imagery	$R^2 > 0.90$ in medium-width rivers	Regional scalability, archive-based reconstruction	Limited resolution for narrow rivers; cloud interference	Medium to large rivers; ungauged basins	[6]
Optical + SAR Fusion with ML	Optical–radar data integration	Satellite optical + SAR-derived indices	Reduced mean relative error (≈0.18 in testing datasets)	Improved robustness under cloud cover	Requires multisensor harmonization	Regional monitoring	[26]
Satellite Optical + Radar Altimetry + ANN	ANN-based discharge merging	Optical imagery + radar altimetry	Daily discharge estimation with strong agreement to gauges	Daily scale monitoring; integrates multiple signals	Dependent on altimetry overpass frequency	Large rivers; global applications	[27]
Satellite Signal + AI Early Warning	Upstream satellite signals + AI	Satellite-derived surface indicators	Improved flood-stage and discharge prediction	Supports early warning systems	Performance varies under low signal-to-noise conditions	Flood-prone regions	[28]

A key differentiating feature lies in operational scalability. Traditional methods are typically constrained to fixed monitoring stations or localized field campaigns [29], whereas satellite-based AI frameworks can extend analysis across broader spatial domains and enable retrospective assessments using archived imagery. Close-range imaging systems offer intermediate scalability, providing continuous monitoring at specific sites without the need for in-stream instrumentation [25,30,31].

Despite these advantages, imagery-based AI approaches remain dependent on reference discharge records for model calibration and validation. Furthermore, their performance is influenced by environmental conditions, image quality, sensor resolution, and hydrological regime. Consequently, rather than constituting a direct replacement for conventional gauging systems, these methods currently function as complementary tools within hybrid monitoring strategies.

Table 4 synthesizes these structural distinctions and provides a comparative framework for understanding the evolving balance between instrument-based hydrometry and

image-driven computational estimation in contemporary discharge research. It should be noted that image-based velocimetry techniques such as Large-Scale Particle Image Velocimetry (LSPIV) were included within the broader Stage 1 corpus as non-intrusive optical approaches. However, these methods were not retained in Stage 2 because they do not inherently integrate machine learning or deep learning architectures for direct discharge inference. Their exclusion reflects the specific methodological focus of the second-stage synthesis rather than a limitation of their hydrometric relevance.

3.4. Justification of the Final Corpus of Image-Based AI Studies

Although the initial database search yielded 2809 records and 249 studies were retained after the first-stage screening, only seven studies were included in the final synthesis of the second stage. This apparent reduction does not reflect a scarcity of research on modern discharge estimation methods, but rather the deliberate application of strict and conceptually focused inclusion criteria designed to isolate state-of-the-art image-based artificial intelligence approaches for river discharge estimation.

The second-stage screening specifically targeted studies that simultaneously fulfilled four methodological conditions: (1) imagery or spatially explicit representations derived from remote sensing or image-based hydrological processing (e.g., close-range optical imagery, UAV-acquired video, or satellite imagery); (2) implementation of machine learning or deep learning architectures (e.g., CNN, LSTM, hybrid CNN–LSTM, or transformer-based models); (3) direct estimation of river discharge as the target variable, rather than intermediate variables such as water level, flow velocity alone, or flood extent; and (4) data-driven validation against reference discharge measurements (e.g., gauge stations, ADCP measurements, or equivalent hydrometric benchmarks). Title-and-abstract screening during the second stage was assisted by ASReview, and final exclusion categorization was performed using predefined, mutually exclusive rule-based criteria to ensure methodological consistency and reproducibility.

A substantial proportion of the 249 studies analyzed in the first stage addressed machine learning applications based solely on hydrometeorological time series, remote sensing analyses not directly linked to discharge quantification, or image-based velocimetry methods without integration of artificial intelligence models. While these studies contribute significantly to the broader evolution of hydrological monitoring, they do not simultaneously satisfy the four methodological conditions established for the second-stage synthesis.

The seven studies retained in the final corpus collectively represent the most methodologically mature and empirically validated implementations of image-based AI discharge measurement identified within the defined temporal scope (2004–2024). Importantly, they encompass diverse image sources (close-range optical imagery, UAV-based data, and satellite imagery), multiple deep learning architectures (including CNNs, LSTMs, hybrid models, and transformer-based frameworks), and varied hydrometric contexts, thereby providing a representative cross-section of current state-of-the-art approaches within this specific research niche.

Notably, the two-stage design of this review mitigates potential scope reduction by first capturing the full methodological evolution of discharge measurement (Stage 1, $n = 249$) before applying a focused synthesis of image-based AI approaches (Stage 2, $n = 7$).

Table 5 presents a structured categorization of the main exclusion groups identified during the second-stage screening process.

As shown in Table 5, excluded studies were systematically classified according to the primary second-stage inclusion criterion they did not fulfill, following predefined and mutually exclusive rule-based criteria consistent with the ASReview-assisted title-and-abstract

screening workflow. This structured approach enhances methodological transparency, minimizes subjective reassignment, and strengthens the internal methodological coherence of the review. The distribution demonstrates that most studies either lacked explicit ML/DL integration, relied solely on non-image-based discharge estimation, or did not directly target river discharge as the modeled variable. Consequently, the reduced final corpus reflects the deliberate methodological focus of Stage 2.

Table 5. Categorization of studies excluded from the second-stage synthesis.

Exclusion Category	Operational Definition	n	Primary Criterion Not Met
Remote sensing-based discharge estimation without ML/DL	Studies estimating discharge from imagery using empirical or physics-based approaches without AI/ML integration	110	No ML/DL implementation
Conventional discharge measurement approaches (non-image-based)	Instrument-based or rating curve-based discharge methods without image input or AI/ML modeling	61	No imagery input; no ML/DL
AI/ML discharge models using time-series only	ML/DL models estimating discharge from hydrometeorological or historical discharge data without image/video input	36	No imagery input
Image-based velocimetry without AI integration	LSPIV, STIV, PIV, or optical flow methods without ML/DL architectures	23	No ML/DL implementation
Studies not directly estimating river discharge (non-Q targets)	Remote sensing and/or AI/ML studies focusing on water level, flood extent, sediment, or velocity-only outputs rather than discharge	12	Discharge not target variable
Total excluded from Stage 2		242	

3.5. Technical Profiling of Stage 2 Image-Based AI Studies

To complement the methodological justification presented in Section 3.4 and to provide a deeper technical synthesis of the retained corpus, this section profiles the seven Stage 2 studies according to harmonized evaluation criteria. While the previous section clarified the exclusion logic, the present analysis focuses on the structural, computational, and operational characteristics of the selected image-based artificial intelligence frameworks for river discharge estimation.

The profiling framework was designed to ensure comparability across studies and includes the following dimensions: image source type, spatial scale of application, AI architecture, target variable definition, validation strategy, reported performance metrics, multi-source data integration, sensitivity to flow conditions, and operational scalability. These criteria allow for a systematic evaluation of how contemporary AI-enabled discharge estimation approaches are implemented in practice and under which hydrological contexts they demonstrate robustness.

As shown in Table 6, all retained studies rely on spatially distributed information derived from close-range optical imagery, UAV-based observations, or medium-resolution satellite data. This confirms that image-derived inputs constitute the foundational data source across Stage 2 studies, even when ancillary hydrometeorological variables are incorporated to enhance model stability.

Regarding AI architectures, the corpus reflects methodological diversity. Convolutional Neural Networks (CNNs) dominate imaging-based applications in controlled or medium-width rivers, whereas transformer-based deep learning frameworks (e.g., RivQNet) demonstrate enhanced capacity for extracting hierarchical spatial features. Additionally, studies integrating support vector regression (SVR) or artificial neural networks (ANNs) in combination with optical and SAR-derived indicators highlight the growing importance of multi-sensor fusion strategies.

Table 6. Technical characterization of the seven Stage 2 AI-enabled image/remote sensing discharge estimation studies included in the final synthesis.

Study	Image Source	Spatial Scale	AI Architecture	Validation Method	Reported Performance	Flow Sensitivity
[13]	Close-range RGB imagery	Medium-width rivers	CNN	Gauge station comparison	NSE ≈ 0.90–0.94	Reduced accuracy at low flow
[5]	Close-range surface imagery	Controlled river sections	Transformer-based DL	In situ discharge gauges	NSE > 0.94	Stable across moderate flows
[6]	Medium-resolution satellite imagery	Large rivers	Deep CNN	Gauge records	R^2 > 0.94	Decrease under low surface contrast
[26]	Sentinel-1 SAR + Landsat 8 + MODIS	Large basin (Yalong River)	SVR	5-fold CV + gauge data	MRE = 0.18; MAE = 18.4 m^3/s; NSE ≈ 0.83	Lower performance during low flow
[27]	Optical satellite + radar altimetry	Large rivers	ANN	Gauge + satellite altimetry	R^2 ≈ 0.83–0.92	Sensitive to seasonal variability
[28]	Satellite brightness temperature	Large rivers	ANN/RBF	Gauge station validation	R^2 ≈ 0.85–0.93	Reduced performance in extreme low flow
[32]	Multi-sensor satellite imagery	Large-scale rivers	ML-based discharge modeling	Gauge comparison	R^2 > 0.90	Sensitivity under extreme hydrologic regimes

In terms of predictive performance, reported Nash–Sutcliffe Efficiency (NSE) values range approximately between 0.83 and 0.97 depending on river morphology, sensor resolution, and flow regime. Satellite-based implementations generally demonstrate high scalability but show reduced sensitivity under low-flow conditions or limited surface contrast. Close-range imaging systems, by contrast, tend to achieve high accuracy in controlled environments but may face operational constraints in remote or hazardous locations.

An important recurring pattern across studies is that multi-source integration (e.g., optical imagery combined with SAR data or ancillary hydrological variables) improves model robustness and reduces prediction error compared to single-sensor approaches. However, these gains come at the cost of increased computational complexity and higher data preprocessing requirements.

Collectively, the retained studies characterize the prevailing implementation patterns of image-based discharge inference across varying spatial scales and sensing configurations. At the same time, they reveal persistent challenges related to training data dependency, generalization across hydrological regimes, sensitivity to extreme low-flow conditions, and the need for rigorous validation against in situ reference measurements.

This technical synthesis provides the empirical foundation for identifying remaining technological gaps and methodological limitations, which are critically examined in the following section.

3.6. Limitations, and Future Directions

Despite the methodological advances demonstrated by the seven Stage 2 studies, several structural limitations persist that constrain the broader operational deployment of image- and remote sensing-based AI discharge estimation frameworks.

A primary limitation concerns the continued reliance on gauge-based discharge records for model training and validation. Although these approaches aim to reduce dependence on intrusive field instrumentation, all retained studies ultimately require in situ discharge measurements for calibration or benchmarking. This dependence limits immediate applicability in fully ungauged basins and highlights the hybrid nature of current AI-based discharge estimation frameworks.

Data dependency represents an additional constraint. Models based on close-range imagery (e.g., [5,13,33,34]), require high-quality visual records under controlled acquisition conditions, while satellite-based approaches (e.g., [6,26–28,32]) depend on consistent surface visibility, adequate spatial resolution, and cloud-free observations. Performance reductions under low-flow conditions or low surface contrast were reported in several cases, indicating sensitivity to hydrological regime and image quality.

Scalability and transferability remain partially unresolved. While satellite-based models demonstrate broader spatial applicability compared to camera-based systems, performance variability across basins suggests that site-specific calibration is often necessary. Cross-basin generalization has not yet been consistently demonstrated across heterogeneous geomorphological settings, and large-scale operational deployment requires further validation across diverse river types. These structural patterns are consistent with the comparative synthesis presented in Table 6, where predictive performance remains closely associated with site-specific calibration and validation against reference discharge records.

Operational deployment further requires technical expertise in image preprocessing, sensor harmonization, model training, and validation against reference discharge measurements. These requirements introduce practical and computational barriers that may limit immediate adoption in resource-constrained monitoring programs.

Another limitation relates to model transparency and uncertainty quantification. The majority of retained studies emphasize deterministic performance metrics such as NSE, R^2, MRE, or MAE. However, systematic uncertainty propagation, confidence interval estimation, and probabilistic discharge prediction are rarely integrated into the modeling framework. This restricts the use of these models in risk-sensitive decision-making contexts such as flood management or water allocation planning.

Future research should therefore prioritize the development of physically consistent and uncertainty-aware AI frameworks. Integrating hydrological constraints into learning architectures, expanding cross-basin validation experiments, and incorporating probabilistic modeling strategies may enhance robustness and operational reliability. Additionally, improved multi-sensor data fusion strategies—combining optical, SAR, and altimetry-derived indicators—show promise for stabilizing performance across hydrological regimes and reducing sensitivity to individual sensor limitations.

While image-based and remote sensing-driven AI methods represent a structural methodological reorientation in discharge estimation, their transition from experimental frameworks to fully operational monitoring systems will require systematic validation, uncertainty integration, and demonstrated transferability across diverse hydrological contexts.

4. Conclusions

This systematic review examined the methodological evolution of river discharge estimation between 2004 and 2024 through a structured two-stage synthesis. The first stage (n = 249) captured the broader historical transition from intrusive, instrument-dependent

hydrometric techniques toward non-intrusive and spatially distributed monitoring approaches. Keyword network and temporal analyses revealed a sustained methodological reorientation after 2018, characterized by the growing integration of remote sensing and artificial intelligence within hydrological inference frameworks.

The second-stage isolated studies that explicitly combine image-derived observations with machine learning or deep learning architectures for direct discharge estimation. These retained studies demonstrate that contemporary image-based AI frameworks operate through structured workflows involving quantitative feature extraction from imagery, data-driven modeling, and calibration against reference discharge records. While close-range and satellite-based approaches differ in spatial scale and operational configuration, both reflect a shift from physically instrumented measurement toward computational inference supported by remotely sensed surface indicators.

Despite demonstrated predictive capability across diverse hydrological contexts, image-based AI approaches remain structurally constrained by calibration and validation requirements. As a result, they currently function as complementary components within hybrid monitoring strategies. Furthermore, limitations related to flow sensitivity, cross-basin transferability, data quality constraints, and limited uncertainty quantification continue to restrict large-scale operational deployment.

Future progress will require moving beyond accuracy-centered model optimization toward physically consistent, uncertainty-aware, and generalizable AI frameworks. Strengthening cross-basin validation, integrating hydrological constraints within learning architectures, advancing multi-sensor fusion strategies, and incorporating probabilistic modeling approaches represent critical next steps. Image-based artificial intelligence holds substantial promise for expanding discharge monitoring capacity, particularly in data-scarce regions; however, its transition from experimental implementation to operational hydrometric infrastructure will depend on systematic validation, transparent workflows, and sustained integration with established hydrological practice.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/earth7020041/s1, Figure S1: Example of duplicate removal in Zotero; Figure S2: Configuration of the ASReview model; Figure S3: Example of labeling of articles as relevant or not relevant; Figure S4: Results of the selection process with ASReview; Figure S5: Results of the selection process using ASReview, comparing the number of articles analyzed and those identified as relevant for the second stage.

Author Contributions: Conceptualization, O.A.G.-V. and D.A.M.-C.; Methodology, O.A.G.-V., A.D.B.-J., M.T.A.-H., A.E.M.-C. and D.A.M.-C.; Data curation, O.A.G.-V., A.D.B.-J., J.G.-P., Y.S. and S.V.-R.; Formal analysis, O.A.G.-V., M.T.A.-H., J.G.-P. and Y.S.; Investigation, O.A.G.-V., A.D.B.-J., A.E.M.-C., J.G.-P., Y.S. and S.V.-R.; Visualization, A.E.M.-C., A.D.B.-J., S.V.-R., J.G.-P. and Y.S.; Validation, M.T.A.-H., A.E.M.-C., J.G.-P., Y.S. and S.V.-R.; Supervision, M.T.A.-H. and D.A.M.-C.; Funding acquisition, D.A.M.-C.; Writing—original draft, O.A.G.-V.; Writing—review and editing, M.T.A.-H., A.E.M.-C., A.D.B.-J., J.G.-P., S.V.-R., Y.S. and D.A.M.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: O.A.G.-V. thanks the Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI) for a Ph.D. scholarship No. 930739 and the Centro de Investigación en Materiales Avanzados S.C. (CIMAV).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lozano Hernández, B.L.; Marín Celestino, A.E.; Martínez Cruz, D.A.; Ramos Leal, J.A.; Hernández Pérez, E.; García Pazos, J.; Almanza Tovar, O.G. A Systematic Review of the Current State of Numerical Groundwater Modeling in American Countries: Challenges and Future Research. *Hydrology* **2024**, *11*, 179. [CrossRef]
2. Barraza, R.L.; Herrera, M.T.A.; Celestino, A.E.M.; Jáquez, A.D.B.; Cruz, D.A.M. Evaluation of the Extreme Precipitation and Runoff Flow Characteristics in a Semiarid Sub-Basin Based on Three Satellite Precipitation Products. *Hydrology* **2025**, *12*, 89. [CrossRef]
3. Bărbulescu, A.; Zhen, L. Forecasting the River Water Discharge by Artificial Intelligence Methods. *Water* **2024**, *16*, 1248. [CrossRef]
4. Biazar, S.M.; Golmohammadi, G.; Nedhunuri, R.R.; Shaghaghi, S.; Mohammadi, K. Artificial Intelligence in Hydrology: Advancements in Soil, Water Resource Management, and Sustainable Development. *Sustainability* **2025**, *17*, 2250. [CrossRef]
5. Ansari, S.; Rennie, C.D.; Jamieson, E.C.; Seidou, O.; Clark, S.P. RivQNet: Deep Learning Based River Discharge Estimation Using Close-Range Water Surface Imagery. *Water Resour. Res.* **2023**, *59*, e2021WR031841. [CrossRef]
6. Hao, Z.; Xiang, N.; Cai, X.; Zhong, M.; Jin, J.; Du, Y.; Ling, F. Remote Sensing of River Discharge From Medium-Resolution Satellite Imagery Based on Deep Learning. *Water Resour. Res.* **2024**, *60*, e2023WR036880. [CrossRef]
7. Costa, J.E.; Cheng, R.T.; Haeni, F.P.; Melcher, N.; Spicer, K.R.; Hayes, E.; Plant, W.; Hayes, K.; Teague, C.; Barrick, D. Use of radars to monitor stream discharge by noncontact methods. *Water Resour. Res.* **2006**, *42*, W07422. [CrossRef]
8. Herschy, R.W. *Streamflow Measurement*, 3rd ed.; Routledge: London, UK, 2009.
9. Uc Castillo, J.L.; Marín Celestino, A.E.; Martínez Cruz, D.A.; Tuxpan Vargas, J.; Ramos Leal, J.A.; Morán Ramírez, J. A systematic review of Machine Learning and Deep Learning approaches in Mexico: Challenges and opportunities. *Front. Artif. Intell.* **2025**, *7*, 1479855. [CrossRef]
10. Uc-Castillo, J.L.; Marín-Celestino, A.E.; Martínez-Cruz, D.A.; Tuxpan-Vargas, J.; Ramos-Leal, J.A. A systematic review and meta-analysis of groundwater level forecasting with machine learning techniques: Current status and future directions. *Environ. Model. Softw.* **2023**, *168*, 105788. [CrossRef]
11. Duan, S.; Ullrich, P.; Shu, L. Using Convolutional Neural Networks for Streamflow Projection in California. *Front. Water. Sec. Water Hydrocomplex.* **2020**, *2*, 28. [CrossRef]
12. Kim, D.Y.; Song, C.M. Developing a Discharge Estimation Model for Ungauged Watershed Using CNN and Hydrological Image. *Water* **2020**, *12*, 3534. [CrossRef]
13. Vanden Boomen, R.L.; Yu, Z.; Liao, Q. Application of Deep Learning for Imaging-Based Stream Gaging. *Water Resour. Res.* **2021**, *57*, e2021WR029980. [CrossRef]
14. Zhang, Y.; Gu, Z.; Thé, J.V.G.; Yang, S.X.; Gharabaghi, B. The Discharge Forecasting of Multiple Monitoring Station for Humber River by Hybrid LSTM Models. *Water* **2022**, *14*, 1794. [CrossRef]
15. Pham Van, C.; Nguyen–Van, G. Three different models to evaluate water discharge: An application to a river section at Vinh Tuy location in the Lo river basin, Vietnam. *J. Hydro-Environ. Res.* **2022**, *40*, 38–50. [CrossRef]
16. Ilhan, A. Forecasting of river water flow rate with machine learning. *Neural Comput. Appl.* **2022**, *34*, 20341–20363. [CrossRef]
17. Muhebwa, A.; Gleason, C.J.; Feng, D.; Taneja, J. Improving Discharge Predictions in Ungauged Basins: Harnessing the Power of Disaggregated Data Modeling and Machine Learning. *Water Resour. Res.* **2024**, *60*, e2024WR037122. [CrossRef]
18. Zhang, J.; Xu, K.; Watanabe, M.; Yang, Y.; Chen, X. Estimation of river discharge from non-trapezoidal open channel using Quickbird-2 satellite imagery. *Hydrol. Sci. J.* **2004**, *49*, 247–260. [CrossRef]
19. Alongi, F.; Pumo, D.; Nasello, C.; Nizza, S.; Ciraolo, G.; Noto, L.V. An automatic ANN-based procedure for detecting optimal image sequences supporting LS-PIV applications for rivers monitoring. *J. Hydrol.* **2023**, *626*, 130233. [CrossRef]
20. Lou, H.; Wang, P.; Yang, S.; Hao, F.; Ren, X.; Wang, Y.; Shi, L.; Wang, J.; Gong, T. Combining and comparing an unmanned aerial vehicle and multiple remote sensing satellites to calculate long-term river discharge in an ungauged water source region on the Tibetan plateau. *Remote Sens.* **2020**, *12*, 2155. [CrossRef]
21. Ilhan, A. Forecasting of volumetric flow rate of Ergene river using machine learning. *Eng. Appl. Artif. Intell.* **2023**, *121*, 105983. [CrossRef]
22. Blanco, A.D.J.; Alarcón, M.T.H.; Marín, A.E.C.; Ramírez, E.N.; Martínez, D.A.C. Extension of LoRa Coverage and Integration of an Unsupervised Anomaly Detection Algorithm in an IoT Water Quality Monitoring System. *Water* **2023**, *15*, 1351. [CrossRef]
23. Liu, W.; Zou, P.; Jiang, D.; Quan, X.; Dai, H. Computing River Discharge Using Water Surface Elevation Based on Deep Learning Networks. *Water* **2023**, *15*, 3759. [CrossRef]
24. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
25. Goswami, G.; Darang, J.; Prasad, R.K.; Mandal, S. Evaluating water availability and flow characteristics for Dikrong river in Arunachal Pradesh using Acoustic Doppler Current Profiler. *Sustain. Water Resour. Manag.* **2024**, *10*, 103. [CrossRef]

26. Wang, X.; Sun, W.; Lu, F.; Zuo, R. Combining satellite optical and radar image data for streamflow estimation using a machine learning method. *Remote Sens.* **2023**, *15*, 5184. [CrossRef]
27. Tarpanelli, A.; Santi, E.; Tourian, M.J.; Filippucci, P.; Amarnath, G.; Brocca, L. Daily river discharge estimates by merging satellite optical sensors and radar altimetry through artificial neural network. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 6536–6549. [CrossRef]
28. Zaji, A.H.; Bonakdari, H.; Gharabaghi, B. Applying upstream satellite signals and a 2-D error minimization algorithm to advance early warning and management of flood water levels and river discharge. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 1028–1042. [CrossRef]
29. Dobriyal, P.; Badola, R.; Tuboi, C.; Hussain, S.A. A review of methods for monitoring streamflow for sustainable water resource management. *Appl. Water Sci.* **2017**, *7*, 2617–2628. [CrossRef]
30. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [CrossRef]
31. Lou, H.; Zhang, Y.; Yang, S.; Wang, X.; Pan, Z.; Luo, Y. A New Method for Long-Term River Discharge Estimation of Small-and Medium-Scale Rivers by Using Multisource Remote Sensing and RSHS: Application and Validation. *Remote Sens.* **2022**, *14*, 1798. [CrossRef]
32. Wang, Y.; Zhang, X.; Liu, J.; Chen, L. Adaptive river flow measurement method based on multi-source data fusion and machine learning. *Water Sci. Technol.* **2024**, *89*, 1028–1043. [CrossRef]
33. Zhen, L.; Bărbulescu, A. Comparative Analysis of Convolutional Neural Network-Long Short-Term Memory, Sparrow Search Algorithm-Backpropagation Neural Network, and Particle Swarm Optimization-Extreme Learning Machine Models for the Water Discharge of the Buzău River, Romania. *Water* **2024**, *16*, 289. [CrossRef]
34. Zlatanović, N.; Gavrić, S. Comparison of an Automated and Manual Method for Calculating Storm Runoff Response in Ungauged Catchments in Serbia. *J. Hydrol. Hydromech.* **2013**, *61*, 195–201. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.